Essays on Heterogeneity over the Business Cycle

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Declaration

I hereby declare that except where specific reference is made to the work of others, the contents of this dissertation are original and have not been submitted in whole or in part for consideration for any other degree or qualification in this, or any other university. This dissertation is my own work and contains nothing which is the outcome of work done in collaboration with others, except as specified in the text.

Rachel Forshaw

30th June, 2020

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Abstract

The three chapters of this PhD thesis look at how heterogeneity and business cycles interact. The first chapter features heterogeneity in the form of multidimentional tasks in occupations, and the composition of job-to-job movers over the business cycle. The second and third chapters focus on heterogeneity in consumption and saving decisions over the business cycle.

Chapter 1 presents a jointly co-authored paper in which we match UK LFS employment transition data to US O*NET data on multidimensional tasks. We present two measures to capture task and skill differences between occupations. We document a set of stylised facts relating to the task and skill content of job transitions over the business cycle in the UK. During recessions, the overall number of transitions decreases and the task content of transitions becomes more similar both in terms of tasks and overall skill requirements, relative to non-recessionary periods. However, we find that the magnitude of all the estimated relationships is very small, and partially offset by selection effects in the types of people who make job-to-job moves during recessions. We do find that those who upskill tend to capture greater wage increases than those who down-skill or whose skills are unchanged. However, we find no cyclical relationship in the wage changes of those who up-skill, down-skill or with no skill change.

Chapter 2 describes the key features of a Bewley-type heterogeneous agent incomplete market models with aggregate and idiosyncratic uncertainty, the Krusell and Smith (1999) model. It reiterates the common result that, in its benchmark form, the model does a poor job of fitting the empirical wealth distribution. It shows that this result is robust to large changes in the key parameters. I show that a commonly

used addition to improve this fit, dispersion in discount factors, implies a contradiction when the model is calibrated to US PSID data before and during the Great Recession. In particular, it implies that the preferences of agents shifted substantially, resulting in a shift of individual policy functions for consumption. However, internal cyclical dynamics of the model imply only a movement in mass along the policy function in recessions. I also show that fitting the empirical fraction of individuals with zero or negative wealth implies that the borrowing constraint should have loosened in the Great Recession, contrary to empirical evidence that the availability of credit fell.

Chapter 3 takes the contradictions of chapter 2, and asks whether the increase in the aggregate marginal propensity to consume could be explained by individual policy functions for consumption shifting over the Great Recession. The mechanism I examine is whether an increase in the variance of income shocks could have caused a shift in the consumption function. This mechanism is also known to shift the consumption function in the model of chapter 2. Using PSID data on consumption and income, I apply the two-step method of Blundell et al. (2008) to first extract the transitory components of consumption and income for individuals in a pre-recession and recession sample. I then use an instrumental variables regression to estimate the marginal propensity to consume out of transitory income at the income quintiles of the distribution. I find that the aggregate marginal propensity to consume increased over the recession, and that the marginal propensity to consume varies across the distribution. However, I do not find evidence that marginal propensities to consume shifted across the income distribution, consistent with consumption functions not shifting. This suggests that increased variance in transitory income is unlikely to explain the contradictory findings of chapter 2.

Lay Summary

The three chapters of this thesis look at the different ways in which taking into account differences across the population or *heterogeneity* can matter for macroeconomic analysis, in particular when we take into account those differences over the business cycle. The first chapter focuses on how occupations can differ in terms of their tasks, how individual characteristics interact with task choices, and how the composition of workers can change with the economic cycle. The second and third chapters look at differences across the population in the proportions of income that different people devote to saving and consumption, and how this interacts with the business cycle.

In the first chapter, I present a work which was completed jointly with a co-author, Aspasia Bizopoulou. In it, we seek to understand if there is a difference in the types of occupations that people do when they are hired in good economic times compared with when they are hired in bad economic times in the UK. Specifically, we are interested in the task and skill content of occupations: tasks being a measure of the types of activities an occupation requires that you do, and skills the level of difficulty at which you complete those tasks at. Good economic times are those when the unemployment rate tends to be low, employers are hiring and in general it is relatively easier to find a job. Conversely, bad economic times are when the unemployment rate tends to be high and it is harder to find a job. It stands to reason that people who are changing their jobs in a bad economic period may make different decisions about the types of occupations they are willing to take relative to good economic times. They may be more willing to take an occupation which is different to their last job in terms of its tasks and skill level in bad economic times, in order to avoid becoming unemployed and likely staying so for a relatively longer time. Alternatively, because the unemployment rate is larger in bad economic times, employers have a larger pool of potential workers to choose from. As such, employers might be able to be more discriminating about potential employees, requiring them to show through previous job experience that they have ability in the tasks and skills for the occupation in question. These two potential effects of recessions work in opposite directions: employees tending to be willing to make larger task and skill moves, and employers only accepting those who make smaller ones. Determining the overall relationship is the aim of this chapter. We find that overall, people that move employers in a recession tend to make smaller task and skill moves than those who move in good economic times. Overall however we find that the effects are very small, and we do not find a difference in the wages of people who move jobs in recession versus those that change jobs in normal economic times.

In chapter two, I present a very influential economic model that is becoming increasingly used in the economics profession. It seeks to represent the different decisions that people make when choosing how much of their income to save and how much to consume. It captures the uncertainty that people face in day-to-day life at the level of the individual: they may lose their job or gain one. It also models uncertainty to do with the state of the economy; there are good and bad economic periods. These two types of uncertainty are also linked: you are more likely to lose your job in a bad economic period than a good one. When people are constrained in how much they can borrow, they have an incentive to save in order to make sure they have a roughly equal amount to consume no matter the state of their employment or the economy. This makes sense: someone who goes from being destitute to winning the lottery overnight would surely be happier overall if they could have spread their winnings evenly over their life. The components of this model taken together results in people making different decisions depending on the state of their life. It also generates wealth inequality, with some people ending up rich and others poor. It is well known that the original version of this model does not do a very good job of fitting data on inequality at a point in time. There are far too few very rich people and not enough poor people. A small modification to the preferences of individuals helps to bridge this gap. If we allow some people to care more about saving for the future, and some to care less, this generates more wealth inequality. Less well known, and the contribution of this chapter, is that with this modification on peoples preferences, the model produces contradictory results for peoples consumption behaviour in recessions. To show this, I take the model to the data from the Great Recession of 2008 in the US. I find the amount of variation in peoples preferences in order to fit the degree of wealth inequality in the good economic times of 2006, and compare this with the variation in preferences to fit wealth inequality in the recession of 2008. I show that this implies a contradiction: both the consumption rates of people in the 2006-fitted model and people in the 2008-fitted model don't react very differently in a recession compared to non-recessionary times. However, comparing the 2006 and 2008 proportion of a change in income devoted to consumption presents a marked difference. In other words, the model with different preferences is not capturing some change that happened over the Great Recession. I also show that, in order to fit with empirical evidence on the fraction of people holding zero or negative overall wealth, we must allow them to borrow greater amounts. This finding is contradictory to both theoretical and empirical findings on the availability of credit in a recession.

In the third and final chapter of this thesis, I and ask whether we can find empirical evidence of what happened in the Great Recession in order for the wealth distribution to change so markedly, that would also generate those same effects in the model of chapter 2. In particular, I ask whether peoples' incomes becoming more temporarily more risky over the recession caused them to change their decision of how much they consume and how much they save out of a change in income. I describe a method to extract changes in consumption and changes in income which were unexpected and temporary from survey data on peoples' total consumption and total income over time. This involves controlling for the parts of consumption and income which are predictable given peoples' characteristics, and an assumption that people cannot perfectly predict the future. In particular, since it is a competing explanation, I control for people who have limited access to credit. My analysis shows that it is unlikely that peoples' incomes becoming more temporarily more risky over the Great Recession would have caused them to systematically change the proportion of a change in income they devoted to consumption.

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Chapter 1

1.1 Introduction

Periods of increased unemployment entail changes to the reallocation processes of the labour market. In particular, there is a well-documented pro-cyclical relationship in the number of job-to-job transitions both in the UK and the US[1]. Yet, while there many studies documenting how the number of transitions decreases in recessions, comparatively less is known about what happens to the content of those transitions in terms of the tasks and skills undertaken as part of occupations. Previous literature has used occupational titles as a proxy for the content of occupations, finding occupational transitions to be strongly pro-cyclical (e.g. Murphy and Topel (1987), Moscarini and Thomsson (2007), Kambourov and Manovskii (2008), Carrillo-Tudela et al. (2014), Carrillo-Tudela et al. (2016)). In this chapter, I present a joint paper with Aspasia Bizopoulou[2] in which we break down occupational titles to actual job tasks and specific skill levels, and show that this strong pro-cyclical relationship is no longer evident: the cycle has little impact on individuals' propensity to change their occupational content. The intuition for why this research finds contradictory results is twofold. Firstly, we are able to calculate the combined impact of recessions on both i) the probability of changing tasks at all as measured by an occupational transition (which we will call the *extensive* effect) and ii) the extent of the task change for those undertaking an occupational change (which we will call the *intensive* effect). Using the McDonald and

[1] See for example, Carrillo-Tudela et al. (2016), Murphy and Topel (1987), Moscarini and Thomsson (2007) and Kambourov and Manovskii (2008)

[2] Senior Researcher, VATT Institute for Economic Research.

Moffitt (1980) decomposition we can estimate that 45 percent of the overall effect we obtain is the result of the latter intensive effect. Previous studies captured only the extensive effect and as such tended to over-estimate the relationship between business cycles and the task content of occupational transitions. The second reason for why we find contradictory results is that there is a selection bias in the types of individuals that change occupations in recessions. Using a Double Hurdle model, we are able to control for this selection effect, which further reduces the magnitude of the overall relationship.

In our analysis we focus on the part of the working population that makes employment-to-employment (henceforth E2E) moves, which represents just over 50% of new hires in the UK. This section of new hires is an important element of business cycles since, adjusting for productivity, the rate of job-to-job transitions is a sufficient statistic for the average real wage in the economy (Moscarini and Postel-Vinay (2016)). Our analysis requires a way to quantify task and skill changes, leading us to focus the first part of the chapter on presenting a suitable measure of change in task composition from the literature which we modify to fit our specific purposes. We also propose a second measure to extract skill level information from the task data. We then detail the empirical methods used to understand the relationship between tasks and skill content of occupational changes and the business cycle. Using unemployment rate as a proxy for fluctuations in economic conditions, we estimate the relationship between an increase in unemployment and task changes and the degree of skill change. Since the decision to change tasks consists of two parts, namely i) the decision to change tasks at all and ii) how big a task move to make, we decompose the estimates to obtain separate figures for each element. Finally, we correlate the changes in up- and downskilling with observed wage changes along different levels of the wage distribution. We find no significant difference in the wages of new hires inside and outside of recessions. We argue that this is due to the cyclical nature of task and skill changes being quantitatively small, and being partially offset by the composition effects of the types of people who get hired in a recession.

Section 1.2 begins by discussing the literature related to this study. In section 1.3 we describe the data that we use. Section 1.4 presents the measures of task and skill difference between occupations. Section 1.5 describes the econometric models used, and section 1.6 reports the results. Finally, section 1.7 concludes.

1.2 Related Literature

Characterising an occupation as a group of separate tasks is a relatively recent but already well-established practice in the literature studying job transitions. Among applied papers, Poletaev and Robinson (2008) are one of the first to map occupational titles to tasks from the US Dictionary for Occupational Titles. They study content difference in occupational switchers, which they define as the situation when the new occupation employs the previous occupation's main skill with much lower or much higher intensity. They find that wage losses are closely associated with switching skill portfolio, in particular a decrease in skills. The key difference to our study is that their sample is of displaced workers, whereas we focus on all job-to-job transitions. In a similar vein, Gathmann and Schönberg (2010) and subsequently Robinson (2018) construct a measure of occupational distance based on tasks, which we modify to use in this paper. Using German administrative data, they find that individuals tend to switch to occupations with similar task requirements, and the change in task composition of occupational moves tends to decrease over time. Our work differs from Gathmann and Schönberg (2010) and Poletaev and Robinson (2008) in that they look at the long-term trends of task change whereas our concern is the variation over the business cycle.

A separate literature studies job transitions over the business cycle. Carrillo-Tudela et al. (2016) look at the propensity for individuals to change careers and find that the probability of a career change co-moves positively with the cycle. In addition, they find that career movers receive higher wages than those who do not change occupations. Devereux (2000) offers an early study of the cyclicality of task assignment, focusing within the firm. He finds that firms tend to re-assign individuals to tasks of lower quality during recessions. Summerfield (2016) shows that recessions lead to an increase in the share of tasks in the economy that are classified as manual. The contribution of the current paper to this literature is to address whether individuals overall tend to move to more or less similar jobs in terms of tasks during recessions, and whether the direction of these moves in terms of the required skill level is affected by economic conditions.

1.3 Data

1.3.1 UK Labour Force Survey (LFS)

We use the UK Quarterly Labour Force Surve (LFS) for the period 2000q1-2010q3. We focus on this time period as our data contain a consistent classification of occupations, Standard Occupational Classification (SOC2010) codes throughout the sample, and it spans the 2008-9 recession.[3] In the LFS respondents are followed over a maximum of five quarters, and in each quarter a fifth of the sample is replaced by an incoming group. For the majority of our analysis, we focus on individuals over two quarters only, with the exception of the wage analysis, where we use the 5 quarter longitudinal sample. The advantage of using the 2 over the 5 quarter is that we have a much larger number of observations, on average 30,000 individuals per quarter, which allows us to include a large number of controls for composition effects.[4] We are able to study job-to-job transitions that involve either no or a very small period of unemployment or inactivity between employment spells.[5]

[3] While occupational classifications are available for the 1990s and 2010s, occupations are classified according to a very different set of criteria. As such, when compared over time it is unclear what is true variation in occupations and what is simply reclassification.

[4] Over time, the LFS has decreased the number of interviewed individuals. In the early years of our sample, each sample has close to 60,000 individuals, while in the later years it drops to about 20,000 per quarter. All estimations and graphs include population weights so that the decreasing number of respondents doesn't bias the results.

[5] The individual may experience a period of unemployment or inactivity of less than a quarter between spells of employment, given the nature of a quarterly survey.

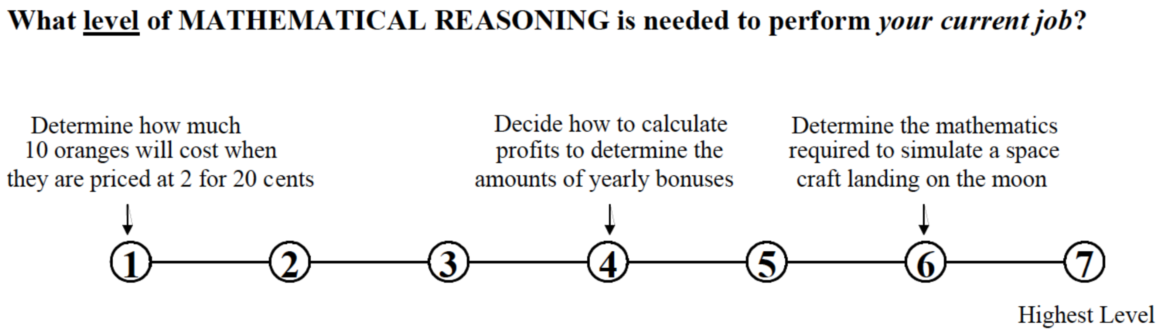


Fig. 1.1 O*NET Example Question

Example question concerning mathematical reasoning from the O*NET, source: US O*NET Abilities Questionnaire

1.3.2 US O*NET

The US Department for Labor's O*NET dataset is a highly detailed survey which provides us with a picture of the tasks that are used in occupations. We standard occupational classifications available in the LFS to match occupations to the US O*NET. Our aim is to obtain a detailed task content and difficulty profile for each occupation and to subsequently measure the distance between different occupations based on similarity of task content and level of skill. We choose to map the O*NET to UK occupational codes as, while some data about the task content of UK jobs exists in the UK Skills Survey, the O*NET is much more suitable for our purposes.[6]

Alongside task data, the O*NET allows us to recover information on the required skill level at which each task is used in each occupation. We refer to this as 'skill level', since the O*NET gives us information about both the type of task in the occupation and the level at which it is performed. To illustrate, figure 1.1 shows the question

[6]The UK Skills Survey contains both labour market variables found in the LFS and task data found in the O*NET, however its sample size is too small for focusing only on job-to-job transitions to run our estimations. For the task data, it would be theoretically possible to average over the observations to get job content for occupations. However, the questions are much more qualitative than the O*NET - variables include 'Importance of looking the part' and 'how often come home from work exhausted'; which, although interesting in their own right, do not readily map to tasks. It also doesn't cover all occupations because they are not sampled. Hillage and Cross (2015) use the method employed in this chapter to map the O*NET to UK SOC codes. They find the method to be robust, to create useful and reasonable data for occupations, and to accord with Skills Survey data in the variables that feature in both.

SOC 2010	Description
2425	Actuary
	Adviser, Economic
	Adviser, Statistical
	Analyst, Campaign
	Analyst, Economic
	Analyst, Political
	Analyst, Quantitative
	Analyst, Statistical
	Analyst, Web
	Assistant, Actuarial
	Assistant, Economic
	Assistant, Statistical
	Bioinformatician
	Consultant, Actuarial
	Consultant, Economic
	Consultant, Statistical
	Controller, Economics
	Controller, Statistical
	Demographer
	Economist

O*NET code	Description	Oral Comprehension
15-2014.00	Statisticians	0.58
19-3011.00	Economists	0.72
15-2011.00	Actuaries	0.61
15-2041.00	Biostatisticians	0.66
15-2021.00	Mathematicians	0.61
43-9111.00	Statistical Assistants	0.64
	Average	0.64

Fig. 1.2 Example of mapping the SOC2010 to the O*NET

The SOC2010 code that covers occupation 'Economist' is 2425 and also covers a number of other occupations, including Actuary and Bioinformatician. Code 2425 maps to multiple O*NET occupations. Taking an average over all of the Oral Comprehension scores for the different O*NET occupations gives a score for the SOC2010 code.

asked for the job task 'mathematical reasoning'. The skill level score ranges from 1 to 7. In this particular example, a skill level of 1 corresponds to "Determine how much 10 oranges will cost when they are priced at 2 for 20 cents", and a score of 6 corresponds to "Determine the mathematics required to simulate a spacecraft landing on the moon", the latter being clearly higher skilled. In section 1.4.1, below, we show the measures used to ascertain the difference between two occupations and to separate out task and skill information.

The O*NET contains task profiles for 974 occupations, which we map onto the 374 SOC2010 occupations of the UK LFS using CASCOT software, discussed below. Since the number of separate occupation categories in the US are almost 3 times as many as the number of occupational categories in the UK Standard Occupational Classification that is used in the LFS, the mapping is not one-to-one, but one-to-many. In order to get a single task vector for each UK SOC code, we follow two steps: first

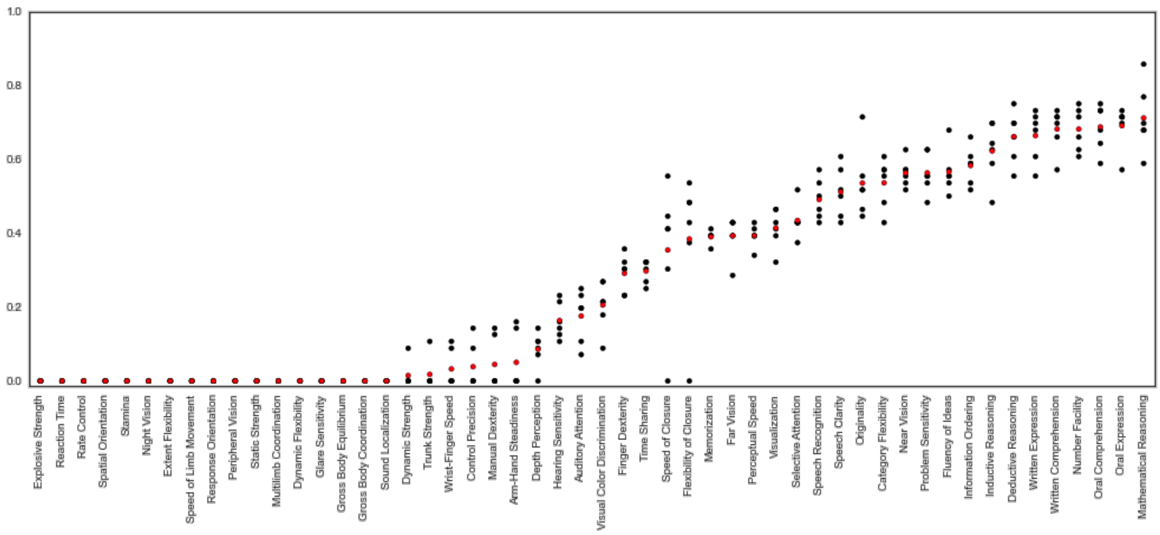


Fig. 1.3 O*NET Task Vector Example - Economist

Example task vector. The y axis lists all the tasks in occupation 2425 (Economist), the x axis is a normalised score of the skill level required for each task. Black dots are the O*NET exact matches for occupation 2425, red dots are the average values across the different possible matches and constitute the final scores that we use in our analysis for this occupation. Source: author's calculations using US O*NET and CASCOT.

we use a confidence-weighted average over all matching O*NET occupations, where the confidence weights for the mapping of O*NET codes to UK SOC codes are provided by the CASCOT software.[7] We obtain a mapping similar to the one shown in Figure 1.2, where SOC code 2425 (left panel) is mapped with 6 different O*NET codes (right panel). Each O*NET occupation has scores for each of the 147 tasks in terms of the level of skill needed to perform a job. In this example, we look at the task 'oral comprehension'. In figure 1.2 SOC code 2425 that covers occupation 'Economist' is mapped with several possible occupations from the O*NET, including 'Actuary' and 'Statistician'. Taking an average over all of the oral comprehension scores for the different O*NET matches gives a single score for this task in the SOC2010 code, which we then repeat for all possible tasks in all possible matches. Figure 1.3 provides an

[7] We use a confidence threshold of 70%, dropping any matches that fall below this confidence level. A visual inspection of the mapping confirms that the matches are sensible.

illustration of the average score for every task that is part of an Economist's portfolio, as calculated in Figure 1.2.

1.3.3 Matching the O*NET task data to the UK LFS

A crucial element in this study is the ability to match UK SOC codes from the LFS with task information from the O*NET. To do this we utilise CASCOT (Computer-Assisted Structured Coding Tool), a software tool developed by the Warwick Institute For Employment Research.[8] CASCOT is a computer program designed to make a semantic match between occupational titles and standard occupational codes. This mapping is created by comparing text descriptions of UK SOC2010 occupations to text descriptions of O*NET occupations.

1.4 Capturing content changes across occupations

1.4.1 Measuring the Change in Tasks

To measure the change in task composition between two occupations we use the measure of angular separation from Gathmann and Schönberg (2010), which has also been used in the innovation literature (Jaffe (1986)). The measure of the change in task composition between two occupations is as follows:

$$\Delta\text{Tasks}_{o,o'} = \left(1 - \frac{\sum_{t=1}^{T}(q_{t,o} \times q_{t,o'})}{\left[(\sum_{t=1}^{T} q_{t,o}^2) \times (\sum_{t=1}^{T} q_{t,o'}^2)\right]^{\frac{1}{2}}}\right) \in [0,1] \tag{1.1}$$

where o, o' is a pair of different occupations, t is tasks, $q_{t,o}$ represents the skill level of a task t within occupation o. Intuitively, the change in task composition between a set of occupations o and o' are compared by measuring the angle between their respective vectors. The scores in the vectors range between 0 (this task is not used in an occupation) and 7 (this task is used at the highest level), which we normalise within $[0,1]$, so that the entire measure is within $[0,1]$. Each occupation is represented

[8] More information available at https://warwick.ac.uk/fac/soc/ier/software/cascot/

by a vector of equal length dimension and each element of the vector gives a task score, i.e. the intensity with which the task is used in the given occupation. Some of the elements of the vector are zeros, since occupations do not use all available tasks. The way we apply equation 1.1 is different to the usage by Gathmann and Schönberg (2010), in which they use data on the fraction of employees using task t in occupation o to comprise $q_{t,o}$. Their data only carries information about the composition of tasks, rather than the skill level, whereas our task vectors include both. Therefore we develop another measure, detailed below in section 1.4.2 which captures the difference in skill level between task vectors.

1.4.2 Measuring the Change in Skills

In our dataset, since the length of the vector for each occupation is determined by the difficulty - or skill level - at which the tasks is required, by measuring its length we can capture the degree of upskilling or downskilling between occupations. We propose the following measure, which takes into account the differences in magnitude between two vectors, to capture the change in skill level:

$$\Delta\text{Skills}_{o,o'} = \left[\left[\sum_{t=1}^{T} (q_{t,o'}^2) \right]^{\frac{1}{2}} - \left[\sum_{t=1}^{T} (q_{t,o}^2) \right]^{\frac{1}{2}} \right] / \sqrt{T} \in [-1, 1] \tag{1.2}$$

Equation 1.2 calculates the difference in length of two occupation task vectors and has range $[-1, 1]$; -1 means that moving occupations results in complete downskilling in every task, 0 means two occupations are equally skilled in every task, 1 complete upskilling in every task.[9] The measure is therefore symmetric, i.e. $\Delta\text{Skills}_{AB} = -1 * \Delta\text{Skills}_{BA}$.

[9] Theoretically, a value of 0 could mean that the two vectors do not have the exact same scores for each task but the differences happen to offset each other perfectly. However, we do not observe this in the data - i.e., no two pairs of different SOC codes return a value of 0.

The Relationship between Skill Level and Wages

In using the ΔSkills measure, equation 1.2, we are assuming that vector length of occupations is a good proxy for skill level of the tasks completed in an occupation. If the measure is capturing skill level we should expect it to be positively correlated with wages. To test this assumption we calculate the skill level for each occupation in the LFS, Skill Level$_o$ = $\left[\sum_{t=1}^{T}(q_{t,o}^2)\right]^{\frac{1}{2}}$, i.e. it is a measure of the vector length of an occupation in the task space. We use this measure in a standard Mincerian wage estimation:

$$lnw_{it} = \alpha + \beta_1 \text{ Skill Level}_o + \sum_k \beta_k X_{k,it} + e_{it}, \tag{1.3}$$

where lnw_{it} are log real gross weekly wages for individual i at time t. The vector X_{it} includes controls for age, age squared, a dummy equal to 1 for female, years of tenure in the current job and dummies for high, medium and low eduction. Skill Level is standardised by subtracting its mean and dividing by its standard deviation to facilitate interpretation. We use the five quarter LFS and take the wage to be the one seen in the last quarter of interview. The sample includes all types of job histories ending with employment in the fifth quarter of interview.

The estimation of Equation 1.3 can been seen in table 1.1. A one standard deviation increase in skill level is associated with a 11% increase in weekly gross real wages. This result suggests that our measure of the length of the vector as a skill difficulty proxy is reasonable since it is strongly positively correlated with wages.

1.4.3 Two-Task Example of the Task and Skill Change Measures

Figure 1.4 provides an illustration of how the ΔTask and ΔSkills measures can provide us with information about the content of occupational moves. We construct a basic example in which there are a total of four different occupations (A, B, C, D) which comprise two tasks: task 1 and task 2. Moving from occupation A, which is highly skilled in task 1 and task 2, to B, which is lowly skilled in both tasks gives a change in task composition of 0, since the tasks are still used in the same proportion. The

	W_{it}
Skill Level	0.11***
	(0.00)
Age	0.07***
	(0.00)
Age^2	-0.00***
	(0.00)
Female	-0.27***
	(0.00)
Years Tenure	0.01***
	(0.00)
High Education	0.70***
	(0.01)
Medium Education	0.27***
	(0.01)
N	84499
R^2	0.337

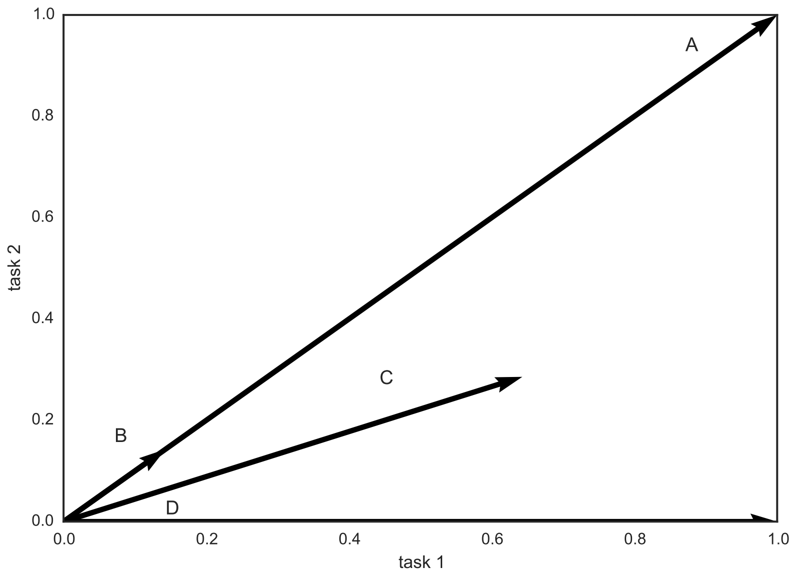
Table 1.1 Estimated Returns to Skills

Notes: Dependent variable is log real gross weekly wages. Esimated on the LFS 5Q sample of full time workers using wages observed in the final interview quarter. Skill Level estimated from linked O*NET data. Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

$\Delta\text{Skills}_{o,o'}$ of -0.86 reflects the fact that occupation B is much lower skilled than A. Moving from occupation C to A represents both a change in tasks and upskilling, whereas the change in tasks from A to D constitutes downskilling. Finally, moving from and to the same occupation A results in zeros for both measures.

1.4.4 The Advantage of Using Task Data

Before proceeding to apply the above measure in our analysis, we take a moment to highlight the advantage of using task data to characterise how the content of two occupations might be different. In mobility studies, authors usually use highly aggregated occupational codes, as in Carrillo-Tudela et al. (2016) who use 1-digit SOC codes, Kambourov and Manovskii (2009) who use 1- and 2- digit occupational codes in the PSID. We argue that such aggregated measures seem to capture very little of the content difference between two occupations. This can be seen anecdotally by looking



Occupation move	$\Delta\text{Tasks}_{o,o'}$	$\Delta\text{Skills}_{o,o'}$
A $\rightarrow$ B	0	-0.86
C $\rightarrow$ A	0.07	0.5
A $\rightarrow$ D	0.29	-0.29
A $\rightarrow$ A	0	0

Fig. 1.4 An example of ΔTasks and ΔSkills with 2 tasks and 5 occupations

at the occupation titles across different 1-digit occupations which can be more similar than transitions within the same 1-digit occupation. For example, moving from being a 'Manager, food and beverage' employee (5436) to working in 'Textiles, garments and related trades' (5419) would not be recorded as a change according to the 1-digit SOC definition of content change whereas the move to 'Manager, public house' (1224) would.

Formalising this observation, figures 1.5 shows the distributions of all potential within- and across-1 digit SOC code occupation moves that can be made in terms of the change in task composition (equation 1.1). We calculate the change in task composition of every occupation pair and plot the score in the left distribution if the first digit of the occupation code differs (an 'across' 1-digit occupation move, which is the type of move usually recorded as a 'content' change in the literature) or the right hand distribution if the first digit of the occupation code is the same (a 'within' 1-digit move, which is not captured as a change in content when using 1-digit SOC codes). If SOC codes capture differences in task content well we should expect the across-distribution (left) to have measures of central tendency to the right of those of the within-SOC (right) code distribution, which would reflect a notion of a large occupational move or 'career change' when making across-code moves. However, while larger moves are slightly more likely in the across-code (left) distribution, we see that the two distributions are remarkably similar.

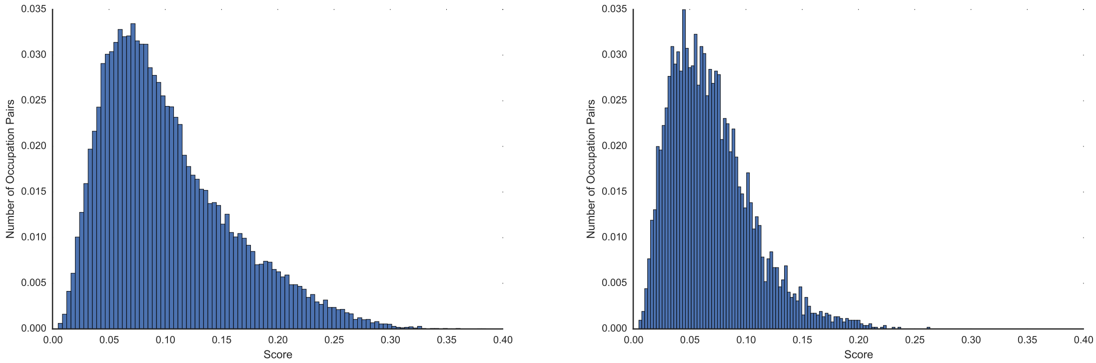


Fig. 1.5 Task distance of potential occupational moves across (left) and within (right) 1-digit SOC codes (excluding zeros)

Quantile	Across 1-digit	Within 1-digit
0.0	0.00	0.00
0.1	0.00	0.00
0.2	0.00	0.00
0.3	0.00	0.00
0.4	0.00	0.00
0.5	0.00	0.00
0.6	0.05	0.04
0.7	0.08	0.05
0.8	0.10	0.07
0.9	0.15	0.10
1.0	0.39	0.26

Table 1.2 Quantiles of task similarity of potential occupational moves across (left) and within (right) 1-digit SOC codes (including zeros)

1.5 Econometric Specifications

We use three different specifications to estimate the relationship between the economic cycle and i) the size of the change in tasks of occupational moves and ii) the absolute level of change in the skills.

1.5.1 Models Without Controls for Selection

4-digit Occupational Level

Our first specification is outlined below in Equation 1.4. We use a Tobit model since our measures of change in task composition and change in skill level are continuous on $[0, 1)$, but with a large portion of the sample (approximately 40%) censored at zero. Individuals censored at zero are those who experience a job transition, but don't change their occupation code. Individuals that do not change codes may still change tasks since even the most detailed 4-digit SOC codes aggregate occupations into groups, as was shown in section 1.3.2. Hence the data is censored, and an OLS estimation would be inconsistent. Below we summarise the model:

$$y_{it,2} = \max(0, \beta_0 + \beta_1 u_t + \sum_j \beta_j X_{j,it,12} + \sum_k \alpha_k \mathrm{Q}_{k,1} + \sum_l \gamma_l \mathrm{R}_{l,1} + \sum_m \delta_m \mathrm{I}_{m,1} + e_{it}) \quad (1.4)$$

Here, i represents individuals; t is time; j are separate individual-level and job-level controls, k are the number of quarters Q, l are the number of regions R, m are the number of industries I; e_{it} is the error term. y_i is the dependent variable, which is either $\Delta\, Tasks_i$ when estimating the relationship between the cycle and the change in task composition of moves or $|\Delta Skills_i|$ when estimating the relationship between the cycle and the absolute change in skill level. We take the absolute value of the change in skill level since we cannot have an upper and lower truncation limit for the Tobit equal to zero (as this would imply no truncated values). A subscript of $_{,1}$ or

$_{,2}$ designates whether the data is taken from the first quarter that a respondent is interviewed, second quarter, and $_{,12}$ denotes both.

Our independent variable of interest is u_t, i.e. the aggregate unemployment rate. We add a set of demographic characteristics, namely age and age squared, marital status, sex, level of education.[10] We also add a set of variables related to the individual's current and previous job: the duration of the previous employment and whether the separation was voluntary/involuntary or related to retirement, as well as controls for whether either job is temporary, part- or full-time, self-employed, and in the public or private sector. Finally, we have a set of controls for the method by which the individual searches for new jobs: through a job centre, ads, direct applications, family/friends, or some other method. The rest of the controls are a set of dummies marking quarters to control for seasonality as well as a set of regional dummies to capture regional differences within the UK.

1-digit Occupational Level

Our second specification addresses the concern that our use of 4-digit occupation codes may obscure the phenomenon that we are investigating. Previous literature has used much more aggregated 1- or 2-digit occupational codes to look at this question, which make occupational change in general less likely, and large occupational changes more likely. To illustrate this point, we graph the probability of occupation change, as defined in Carrillo-Tudela et al. (2016), in which the probability of career change at the k-digit (k=1,2,3,4) is estimated as:

$$\text{Prob Career Change}^k = \frac{E2E_m^k}{E2E_s^k + E2E_m^k}$$

where $E2E_m^k$ is the number of individuals that changed jobs and moved k-digit occupation; and $E2E_s^k$ is the number of individuals that changed jobs and did not move

[10] We split education into low, medium and high. In the low category we only include individuals with no qualifications whatsoever; in the middle we include those with at least an Entry Level Qualification and at most A levels (a UK pre-requisite for university entry); and in the high we include all those with any qualification above A levels.

their k-digit occupation. For example, an Economist is in occupational code 2 at the one-digit level. If she changed occupations to become a Florist (SOC 5 at the one-digit level), this would be classed in the numerator as an E2E move. If, however, she became a management consultant (occupational code 2), this would be classed in the denominator as a one-digit stay.

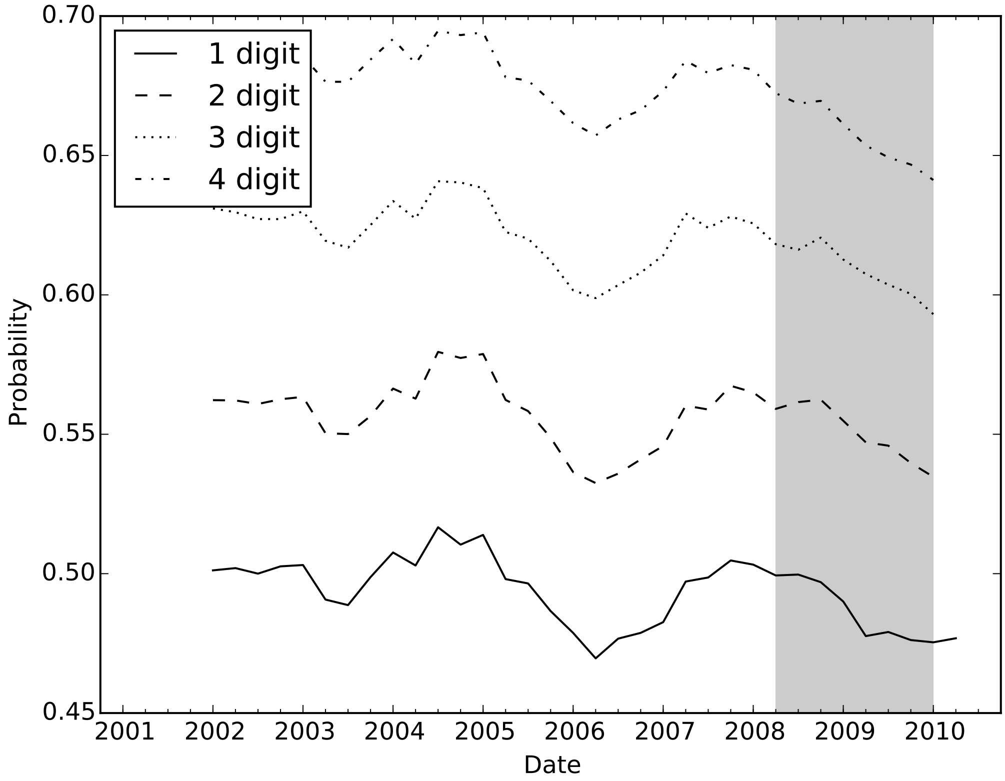


Fig. 1.6 Probability of Career Change at 1-,2-,3- and 4-digit Occupation Codes

Five quarter moving average of the probability of career change as estimated as the ratio of E2E movers that changed a) 1-digit, b) 2-digit, c) 3-digit, d)4-digit occupation to those E2E that stayed within the respective occupational digit.

To make our analysis as comparable to previous results as possible, we also estimate equation 1.4 with dependent variables $\Delta Tasks_i$ and $|\Delta Skills_i|$ aggregated to the 1-digit occupational code level. To do so, we calculate the average potential task or skill move from all 4-digit occupational codes with first digit j to all 4-digit occupational codes with first digit k to be the task or skill change for any moves between $j\star\star\star$ and

$k{\star}{\star}{\star}$. Moves from 4-digit code $j{\star}{\star}{\star}$ to the same first digit $j{\star}{\star}{\star}$ will have task and skill distance zero. For example, a move from 1121 to 2462 has the same task distance, 0.07 (the average task change of all possible moves from occupations with first digit 1 to first digit 2), as a move from 1221 to 2444.

Table 1.3 Difference in Means of E2E Sample In and Outside Recession

Recession	0	1	Difference
Female	0·51	0·50	−0·006
	(0·00)	(0·01)	(0·013)
Age of respondent	33·67	35·59	1·920***
	(0·10)	(0·31)	(0·318)
Married	0·41	0·46	0·045***
	(0·00)	(0·01)	(0·013)
Tenure (months)	39·21	46·93	7·719***
	(0·49)	(1·77)	(1·624)
Full Time in Previous Job	0·71	0·73	0·015
	(0·00)	(0·01)	(0·012)
Full Time in Current Job	0·76	0·75	−0·009
	(0·00)	(0·01)	(0·011)
Temporary in Previous Job	0·15	0·12	−0·028***
	(0·00)	(0·01)	(0·009)
Temporary in Current Job	0·18	0·17	−0·002
	(0·00)	(0·01)	(0·010)
Self Employed in Previous Job	0·03	0·04	0·013***
	(0·00)	(0·01)	(0·005)
Self Employed in Current Job	0·08	0·09	0·017**
	(0·00)	(0·01)	(0·007)
Public Sector in Previous Job	0·13	0·16	0·023***
	(0·00)	(0·01)	(0·009)
Public Sector in Current Job	0·15	0·20	0·046***
	(0·00)	(0·01)	(0·010)
High Education	0·20	0·27	0·073***
	(0·00)	(0·01)	(0·011)
Medium Education	0·73	0·69	−0·042***
	(0·00)	(0·01)	(0·012)
Low Education	0·08	0·05	−0·030***
	(0·00)	(0·01)	(0·007)
Search Method: Not Looking	0·92	0·91	−0·007
	(0·00)	(0·01)	(0·007)
Search Method: Job Centre	0·02	0·01	−0·007**
	(0·00)	(0·00)	(0·003)
Search Method: Applying to Ads	0·05	0·06	0·012**
	(0·00)	(0·01)	(0·006)
Search Method: Direct Application to Employers	0·01	0·01	−0·000
	(0·00)	(0·00)	(0·002)
Search Method: Ask Friends/Relatives	0·01	0·01	0·001
	(0·00)	(0·00)	(0·002)
Other Job Search Method	0·01	0·01	0·001
	(0·00)	(0·00)	(0·002)
Involuntary Separation	0·23	0·29	0·061***
	(0·00)	(0·01)	(0·011)
Voluntary Separation	0·48	0·45	−0·036***
	(0·00)	(0·01)	(0·013)
Other Separation	0·29	0·27	−0·026**
	(0·00)	(0·01)	(0·012)
N	15514	1594	17108

Notes: Difference in longitudinal-weighted means inside=1 and outside=0 of recession for E2E movers in the LFS 2Q sample. Recession periods defined using UK ECRI indicator. Significance levels: * < 10% ** < 5% *** < 1%. Standard errors in parentheses. Source: author's calculations.

1.5.2 Selection Controls

One issue that arises in the estimation of equation 1.4 is the possibility of selection bias. Our population of interest consists of individuals undertaking a job-to-job transition. Since the volume of job transitions decreases in recessions, the composition of those who make a job-to-job transition in a recession is likely different to those who do so in normal economic conditions. Table 1.3 confirms there are significant differences in observable characteristics between the recession and and non-recession samples. Those that make a job-to-job transition in a recession are older, more likely to be married and have longer tenure. Fewer are in temporary roles for their previous or current job, and a larger fraction are self employed or work for the public sector in either their previous or current job. More are high-educated and a lower fraction are medium- or low- educated. Fewer have quit (made a voluntary separation) from their previous employer, and a larger fraction have been fired (made an involuntary separation).

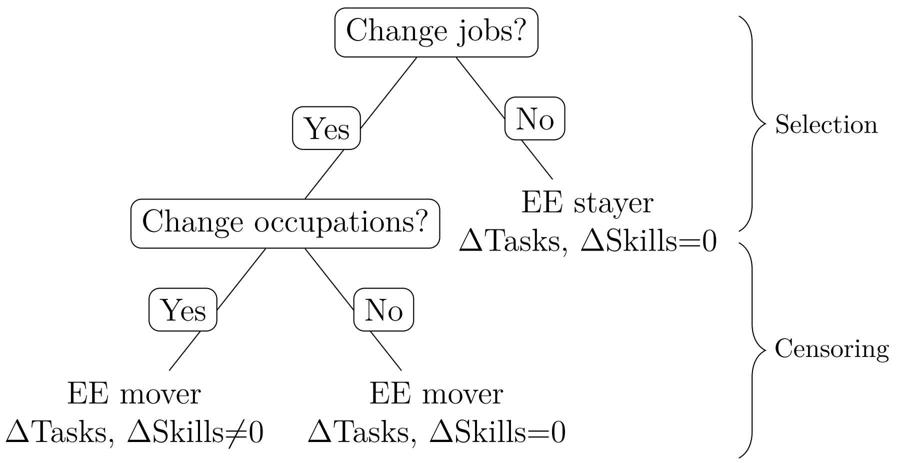


Fig. 1.7 Illustration of Double Hurdle model

First step: whether an individual changes jobs. Second step: whether an individual changes occupations (whether they have a task and skill change.)

While we control for these observable composition changes in our estimations, a question remains about whether this selected sample will bias estimates if there is remaining unobserved heterogeneity. To explore this, we adopt a third regression specification using a Double Hurdle model developed by Dong and Kaiser (2008). This model captures the intensive and extensive effects of recessions on job transitions, illustrated in figure 1.7. The first hurdle, is a Probit model, capturing whether an individual decides to change jobs or not. If they do not change jobs, their Δ Tasks and Δ Skills will be always be zero. In the second hurdle, if the individual has changed jobs, they must decide whether to change occupations. If they change occupations, Δ Tasks and Δ Skills will be non-zero. If they do not change occupations, their Δ Tasks and Δ Skills will appear as zero in the data. Note though, there is the same censoring issue as discussed in section 1.5.1 - they may change tasks and skills but not occupation codes - so for this second step a Tobit model is also the correct specification. Concretely, the equations of the Double Hurdle model are:

$$EE_{it,2} = \tilde{\beta}_0 + \tilde{\beta}_1 \text{Available}_{t,1} + \sum_j \tilde{\beta}_j \hat{X}_{j,it,1} + \sum_k \tilde{\alpha}_k \mathrm{Q}_{k,1} + \sum_l \tilde{\gamma}_l \mathrm{R}_{l,1} + \sum_m \tilde{\delta}_m \mathrm{I}_{m,1} + \tilde{e}_{it} \tag{1.5a}$$

$$y^*_{it,2} = \max(0, \check{\beta}_0 + \check{\beta}_1 u_t + \sum_j \check{\beta}_j X_{j,it,12} + \sum_k \check{\alpha}_k \mathrm{Q}_{k,1} + \sum_l \check{\gamma}_l \mathrm{R}_{l,1} + \sum_m \check{\delta}_m \mathrm{I}_{m,1} + \hat{\lambda}_t + \check{e}_{it}) \tag{1.5b}$$

Equation 1.5a is the Probit selection model which has dependent variable EE equal to one if an individual changes jobs between the first and second quarter of interview, and zero otherwise. Note that the control variables $\hat{X}$ differ from those in the structural equation, since we include only first-period controls for characteristics of the respondent's previous job. We also omit search method as only those that changed jobs were asked which search method they used. The Double Hurdle model is similar to the control function approach advanced by Heckman (1979), but allows the selection and structural equations to be governed by distinct processes. As in a Heckman model, we allow the errors of the first and second hurdles to be correlated. As such, to avoid multicollinearity issues we also include the instrument *Available*, whether the individual is available to start work in the next two weeks. The instrument for the selection equation is a dummy which captures whether an individual is available to start work in the next two weeks. This will be equal to one if the respondent is looking for a new job, is waiting to start a new job or would like a new job but has not yet started searching and would be able to start a job in the next two weeks. This instrument is highly predictive of the dependent variable in the selection equation - whether the individual changed jobs between the first and second quarter of their survey. However, it should not have any bearing on the size of the task or skill change that an individual makes after changing jobs, the dependent variable in the two structural equations. Equation 1.5b is the Tobit structural model with dependent variables $y^*_{it,2}$ either $\Delta Tasks_i$ or $|\Delta Skills_i|$. Contrary to equation 1.4, the y^* includes observations in which an individual did not make a job change, meaning a $\Delta Tasks_i$ or $|\Delta Skills_i|$ equal to 0. Otherwise this specification is the same as 1.4, with the addition of the estimated inverse Mills ratio obtained from estimating equation 1.5a, $\hat{\lambda}$ to control for selection.

1.6 Results

1.6.1 Changes in Tasks and Skills over the Cycle

To control for the changing composition of E2E transitions over the cycle, we estimate the Tobit model of equation 1.4. Results are shown in model (1) of table 1.4. We see that an increase in the unemployment rate of one percentage point is associated with .02 of a standard deviation reduction in task change.[11] The magnitude of this relationship is very small. To put this into context, we estimate that the conditional average of ΔTask Change is .04[12]. An example of a move with ΔTask composition equal to .04 is from 4159 'Fraud Inspector' to 3533 'Insurance Underwriter'. During the 2008 recession, the unemployment rate increased by approximately 2.5 percentage points. The estimated standard deviation of ΔTask composition, conditional on the controls listed in section 1.5, is .04. An increase in the unemployment rate by 2.5

[11]-.04 times the APE factor, .62

[12]Conditional on the compositional controls listed in table 1.4.

percentage points would therefore correspond to an approximate change of:

$$\underbrace{2.5}_{\Delta Xu} * \underbrace{-.02}_{\frac{\partial \widehat{E(y|X)}}{\partial Xu}} * \underbrace{.04}_{\widehat{E(\sigma|X)}} = -.002$$

In our example, this would be an occupational move with ΔTasks=.04 -.002 = .038. An example of such a task move is 3532 'Insurance Broker' to 4132 'Administrative Officer, Insurance'. Both of these examples are small occupational moves, and there seems to be minimal difference between the two types of moves.

In terms of the absolute change skill level (i.e. when $y_i = |\Delta Skills_i|$), the effect is in the same direction and of a similar magnitude. An increase in the aggregate unemployment rate corresponds to a -.02 change in skill level.[13] This effect is similarly economically insignificant.

[13]-.03 times the APE factor,.62, table 1.4

Table 1.4 Changes in Tasks and Skills over the Cycle

	(1) Tobit at 4-digit		(2) Tobit at 1-digit		(3) Double Hurdle at 4-digit			
	Δ Tasks	Δ Skills	Δ Tasks	Δ Skills	Δ Tasks	EE	Δ Skills	EE
Unemployment Rate	-0.037**	-0.030*	-0.049**	-0.049**	-0.018	0.048***	-0.0028	0.082**
	(0.017)	(0.017)	(0.024)	(0.024)	(0.025)	(0.019)	(0.027)	(0.033)
Female	0.042	0.11***	0.042	0.042	-0.19**	0.36***	0.14***	0.28***
	(0.027)	(0.027)	(0.037)	(0.037)	(0.079)	(0.030)	(0.050)	(0.050)
Age	-0.043***	-0.035***	-0.045***	-0.045***	-0.046***	-0.015**	-0.045***	-0.014
	(0.0067)	(0.0066)	(0.0091)	(0.0091)	(0.0098)	(0.0071)	(0.011)	(0.013)
Age squared	0.45***	0.34***	0.47***	0.47***	0.59***	0.11	0.52***	0.091
	(0.089)	(0.087)	(0.12)	(0.12)	(0.13)	(0.095)	(0.15)	(0.18)
Married	-0.030	-0.040	-0.041	-0.041	-0.067	-0.0047	-0.097**	0.052
	(0.029)	(0.029)	(0.041)	(0.041)	(0.043)	(0.034)	(0.047)	(0.061)
High Education	-0.25***	-0.21***	-0.22***	-0.22***	-0.11	-0.11*	-0.19**	0.036
	(0.053)	(0.052)	(0.075)	(0.075)	(0.077)	(0.063)	(0.082)	(0.12)
Medium Education	-0.069	-0.058	-0.042	-0.042	0.11*	-0.16***	0.058	-0.20**
	(0.045)	(0.044)	(0.064)	(0.064)	(0.068)	(0.052)	(0.073)	(0.087)
Tenure	-0.026***	-0.020***	-0.020**	-0.020**	-0.030***	0.039***	-0.024**	0.075***
	(0.0055)	(0.0054)	(0.0076)	(0.0076)	(0.011)	(0.0063)	(0.012)	(0.014)
Full Time in Previous Job	-0.25***	-0.20***	-0.31***	-0.31***	-0.22***	-0.10***	-0.23***	-0.048
	(0.032)	(0.032)	(0.044)	(0.044)	(0.047)	(0.032)	(0.048)	(0.051)
Full Time in Current Job	0.070**	-0.040	0.0051	0.0051	0.13***		-0.022	
	(0.032)	(0.032)	(0.045)	(0.045)	(0.036)		(0.038)	
Temporary in Previous Job	0.050	0.040	0.060	0.060	-0.021	0.081**	0.0096	0.11
	(0.037)	(0.036)	(0.052)	(0.052)	(0.054)	(0.040)	(0.059)	(0.068)
Temporary in Current Job	0.18***	0.14***	0.15***	0.15***	0.21***		0.16***	
	(0.032)	(0.033)	(0.045)	(0.045)	(0.037)		(0.038)	
Public Sector in Previous Job	-0.038	0.033	-0.063	-0.063	-0.089	-0.045	-0.0018	-0.14
	(0.047)	(0.048)	(0.068)	(0.068)	(0.066)	(0.053)	(0.082)	(0.10)
Public Sector in Current Job	0.19***	0.18***	0.12**	0.12**	0.14***		0.14***	
	(0.035)	(0.035)	(0.049)	(0.049)	(0.040)		(0.042)	
Self Employed in Previous Job	0.39***	0.20***	0.35***	0.35***	0.48***	-0.12**	-0.018	0.12
	(0.069)	(0.063)	(0.095)	(0.095)	(0.094)	(0.058)	(0.11)	(0.14)
Self Employed in Current Job	0.27***	0.091**	0.27***	0.27***	0.54***		0.18***	
	(0.050)	(0.046)	(0.063)	(0.063)	(0.056)		(0.053)	
Involuntary Separation	-0.083***	-0.077**	-0.20***	-0.20***	-0.060	-0.0052	-0.010	-0.048
	(0.032)	(0.032)	(0.045)	(0.045)	(0.045)	(0.035)	(0.049)	(0.061)
Other Separation	-0.10***	-0.086***	-0.16***	-0.16***	-0.041	-0.053*	-0.036	-0.069
	(0.028)	(0.028)	(0.039)	(0.039)	(0.041)	(0.031)	(0.046)	(0.053)
Search Method: Job Centre	0.23***	0.21**	0.26**	0.26**	0.071		0.045	
	(0.089)	(0.087)	(0.12)	(0.12)	(0.10)		(0.10)	
Search Method: Advertisements	0.32***	0.26***	0.36***	0.36***	0.30***		0.20***	
	(0.055)	(0.056)	(0.075)	(0.075)	(0.063)		(0.063)	
Search Method: Direct Application	-0.0054	-0.037	0.0044	0.0044	-0.17		-0.20	
	(0.12)	(0.12)	(0.17)	(0.17)	(0.15)		(0.15)	
Search Method: Family/Friend	0.12	0.12	-0.058	-0.058	0.0056		-0.042	
	(0.17)	(0.15)	(0.22)	(0.22)	(0.17)		(0.17)	
Search Method: Other	0.085	0.20	0.37*	0.37*	-0.16		-0.021	
	(0.14)	(0.15)	(0.20)	(0.20)	(0.17)		(0.17)	
Available						0.15***		0.19***
						(0.031)		(0.049)
λ					-0.10		0.21	
					(0.51)		(0.47)	
Quarters	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regions	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industries	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	17130	17130	17130	17130	28592		28592	
APE	.64	.64	.47	.47	.42		.42	
pseudo R^2	0.023	0.023	0.022	0.022	0.0137		0.0223	
Log llik.	-21672272.2	-21568016.8	-20294343.9	-20294343.3	-34467.8		-34498.6	

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

(1) Tobit at the 4-digit occupation category level. (2) Tobit at the aggregated 1-digit occupation category level (3) Double Hurdle at the 4-digit occupation category level. The sample in the selection equation of specification (3) is all individuals aged 16-64 years old over the period 2000q1-2010q3 and employed in both the first and second quarter of their survey. The sample in all other other specifications have the additional restriction that individuals undertook a job transition over two quarters (i.e., changed employers). The coefficient on age squared is multiplied by 1000. The reference category for education is Low Education; for Job Separation it is 'Voluntary'; for Job seeking method it is 'Not Looking'. The regression includes seasonal, regional and industry fixed effects. Coefficients should be multiplied by the APE factor to obtain correct marginal effect. Standard errors in parentheses.

With the addition of task data to occupations, we are able to look not just at the *probability of changing occupations* during recessions but also the *extent of the change* of the task content. McDonald and Moffitt (1980) show that the marginal effect of a Tobit model can be decomposed as follows:[14,15]

$$\underbrace{\frac{\partial E(y|X)}{\partial Xu}}_{\text{Total marginal effect}} = \underbrace{P(y>0|X)}_{\substack{\text{Probability of changing}\\ \text{occupations}\\ =.64}} \underbrace{\frac{\partial E(y|X,y>0)}{\partial Xu}}_{\substack{\text{Change in expected task move}\\ \text{given occupation move}\\ \text{following a change in}\\ \text{the unemployment rate}\\ =-.0007}} + \underbrace{E(y|X,y>0)}_{\substack{\text{Expected task move}\\ \text{given occupation move}\\ =.06}} \underbrace{\frac{\partial P(y>0|X)}{\partial Xu}}_{\substack{\text{Change in probability of}\\ \text{occupation move}\\ \text{following a change in}\\ \text{the unemployment rate}\\ =-.01}} \tag{1.6}$$

Of particular interest to this chapter is the relationship between the unemployment rate and the change in task composition given that there is an occupation change, i.e. the term $\frac{\partial E(y|X,y>0)}{\partial X_u}$, as opposed to the term $\frac{\partial P(y>0|X)}{\partial X_u}$ which only measures the impact on the probability of changing occupation and has previously been shown to be negative and economically significant. Here, we estimate this change in probability to still be negative, but it is not as large in magnitude as in previous research. This is due to our definition of occupational change being much more granular, at the 4-digit occupational code rather than 1-digit as in previous work. Using $z \equiv X\beta/\sigma$ and the cumulative normal distribution function $F(z) \equiv P(y>0|X)$ and dividing both sides of equation 1.6 by $F(z)\beta_u$, we can get the expression:

$$\frac{\partial E(y|X,y>0)}{\partial X_u} = \pi_u * \beta_u \tag{1.7}$$

where:

$$\pi_u = (1 - zf(z)/F(z) - f(z)^2/F(z)^2)$$

is the fraction of the mean total response attributable to the response from those who change occupations *and* tasks. We obtain the estimate of this fraction $\hat{\pi}_u$, by calculating $\hat{z}$ using our reduced-form estimates in $\hat{z} = \sum_{i=1}^{N} F^{-1}(X_i\hat{\beta}_u/\hat{\sigma})$ as:

$$\hat{\pi}_u = 44.81\%$$

[14] See appendix A.1 for details

[15] Note that, unlike the reported Tobit marginal effects in table 1.4, for ease of interpretation of probabilities this decomposition is not standardised and so it sums to the unstandardised marginal effect, -.001.

This is a substantial fraction attributed to the intensive margin of those who switch occupations (the *extent of task change*). It explains why studies look at only the extensive margin of whether to make an occupational move or not will miss a large portion of the overall relationship between recessions and occupational content changes.

Regression specification (2) in table 1.4 shows further that our results are not entirely driven by our use of more granular occupational codes. Model (2) shows the same Tobit model as (1) but with task and skill moves aggregated to 1-digit occupational categories. While the coefficient on the unemployment rate is larger in magnitude, as expected, it remains economically insignificant.

Regression specification (3) in table 1.4 further controls for selection bias using a Double Hurdle model. Controlling for the selection effects of those who move occupations in recessions, we see that the coefficient on the unemployment rate is smaller in magnitude for both task and skill moves, and is now statistically insignificant.

In each specification control variables are, for the most part, significant, and in a number of cases they are a magnitude larger than the estimated coefficient on the unemployment rate. Older individuals (*Age*) tend to make smaller task and skill moves, consistent with the idea that individuals tend to specialise over their careers. For the same reasons, those with a higher relative to lower education level (*High Education*), and those with greater tenure (*Tenure*) tend to make smaller task and skill moves. Being full time relative to part time in their first quarter job (*Full Time in Previous Job*) is associated with much lower task and skill moves in all specifications, and at a magnitude of approximately ten times that of the effect of recessions. This suggests that full time workers are much less flexible in changing the content of their jobs when moving employers than part time workers are. Similarly, being fired from a first quarter job (*Involuntary Separation*) is associated with much smaller task and skill moves than quits. If an individuals' second quarter recorded occupation is temporary rather than permanent (*Temporary in Current Job*), this is associated with much larger task and skill moves. Again this association is an order of magnitude greater than that of recessions. The same is true for having a public sector rather than private sector job in the second quarter (*Public Sector in Current Job*), being self employed in either the first or second quarter of interview (*Self Employed in Previous/Current Job*) and applying to jobs via Job Centres (*Search Method: Job Centre*) and Advertisements (*Search Method: Advertisements*) relative to not searching for a job.

1.6.2 Real Wage Changes

Table 1.5 shows the average of the quarterly time series of the real wage changes for those that make employment transitions, broken down by period (recession/non-recession) and skill change type (upskill, downskill, unchanged). We focus on skills for this analysis, since if there is a skill change there has necessarily been a task change; furthermore, the skills data allows us to separate into upskilling and downskilling which will have contrasting consequences for wages. Since the LFS only reports wages in the first and fifth quarter of interview, we use the five quarter sample for this analysis. Necessarily the sample size is much smaller, which means we do not have enough observations to look at the conditional wage distribution in terms of the observable characteristics considered in section 1.6.1. However, we are able to include job transitions that feature up to three quarters of unemployment or inactivity which means we cover the majority of all new hires and should therefore be less subject to selection biases.

We see that for the 25th percentile of the wage distribution, all job transitions result in a decrease in real wages whereas for the 75th all transitions result in an increase, a fact that is consistent with the literature on wage polarisation and sorting.[16] We observe that transitions resulting in upskilling have a higher real wage change significant at the 5% level across the real wage distribution. For the median earner, this wage change is approximately 3 percentage points higher for upskilling than downskilling, or approximately 6 percentage points higher for upskilling versus unchanged skill. Note that interestingly, downskilling tends to command a higher wage than unchanged skills for the median worker, a statistic which is consistent with existing literature finding that an occupational change comes with a wage premium (e.g. Carrillo-Tudela et al. (2016)).

In the 2nd and 3rd panels of Table 1.5, we split the sample into recession and non-recession to highlight the observed differences in wages for those changing the level of their tasks during and outside of recessions. We run a set of t-tests for difference in means in table 1.6 to test if the changes in wages are significantly different. We find that mean wage changes are not significantly different within and outside of recessions for those who upskill, downskill, or whose skills remain unchanged. This should not be a surprise: our estimated relationship between the business cycle and task changes is economically small and so should not be a factor in wage determination.

[16] See for example, Autor et al. (2003); Autor et al. (2008); Goos and Manning (2007); Goos et al. (2009); Cavaglia and Etheridge (2017) for the polarisation literature and Groes et al. (2014) for sorting.

Table 1.5 Real Wage Change

Percentile	Whole Sample			Recession			No Recession		
	Upskill	Downskill	Unchanged	Upskill	Downskill	Unchanged	Upskill	Downskill	Unchanged
25th	-6.97	-10.84	-6.03	-7.32	-11.67	-5.47	-6.75	-10.31	-6.39
50th	5.92	3.35	1.41	6.91	3.66	2.09	5.31	3.16	0.98
75th	30.74	23.69	12.36	33.82	25.34	13.53	28.82	22.66	11.63

Averages of the quarterly time series of percentiles of real percentage wage change compared to previous job over the time periods listed. Using 5Q LFS survey, 'Total' defined as employment to employment transitions with a period of 1-3 quarters of inactivity (EIE), unemployment (EUE) or direct job-to-job (EE). EIE not detailed separately due to small sample size. Deflated using the UK consumer price index, whole sample 2000q2- 2010q3 . Recession periods defined using UK ECRI indicator.

Table 1.6 Real Wage Change Significance Tests

Percentile	Upskill vs. Downskill	Upskill vs. Unchanged	Downskill vs. Unchanged	Upskill Recession vs. Upskill No Recession	Downskill Recession vs. Downskill No Recession	Unchanged Recession vs. Unchanged No Recession
25th	[5.99 0.]	[-1.8 0.07]	[-9.33 0.]	[-1.21 0.23]	[-1.79 0.08]	[1.81 0.07]
50th	[2.89 0.]	[6.44 0.]	[3.11 0.]	[0.83 0.41]	[-0.01 0.99]	[1.73 0.09]
75th	[2.74 0.01]	[8.96 0.]	[6.75 0.]	[0.93 0.36]	[0.63 0.53]	[1.94 0.06]

Significance test of difference in means of real wage change. First statistic in brackets is t-test,second is two-tailed p-value. H_0: Two samples have identical expected values.

1.7 Conclusion

In this chapter I presented the results of a joint work in which we study the extent to which the change in task composition of job transitions is sensitive to cyclical fluctuations. We use data from the UK Labour Force Survey to study job-to-job transitions and map occupations to their task content using the US O*NET dataset. Using measures of task and skill distance we study whether increases in the unemployment rate are associated with changes in the content of the occupations of new hires. Contrary to previous research, we find little evidence for an economically significant relationship. Unlike previous research, we focus on observed changes in the task content and skill level of job transitions, not only on changes in occupational category. This allows to estimate the combined effect of both the extensive (on the probability of changing occupation), as well as the intensive margins (the extent to which job content changes), the latter being novel to the current research. We find that this latter effect is much smaller, and comprises 45 percent of the overall effect. Taking into account both extensive and intensive effects, we find that the overall association of task and skill changes and business cycles is weak, especially when controlling for selection effects. We also find that wage increases resulting from job transitions are more strongly predicted by one's starting point on the wage distribution and eventual upskill or downskilling transition, and not by economic conditions. In the context of designing policies to improve job search, it is useful to know that factors related to the individual characteristics and job conditions are much more strongly associated with task and skill reallocation in job-to-job transitions than economic shocks.

Chapter 2

2.1 Introduction

In this chapter, I document the business cycle properties of the canonical model of saving with heterogeneous agents, the Krusell-Smith (KS) model. While a highly cited and influential paper, its popularity is due more to its novel method of solving an analytically non-tractable problem than down to its realism in representing the world. In this chapter I explore its shortcomings in terms of empirical realism - namely, in its benchmark form, it does a poor job of fitting the cross sectional wealth distribution both at a moment in time and its dynamics over the cycle. I explore a commonly used method to fit empirical evidence about the wealth distribution: dispersion in discount factors. When two calibrations of the model fitting the wealth before and during the Great Recession are compared with the model's internal business cycle dynamics, I show that there are two contradictions. Firstly in terms of the distribution of agents' marginal propensities to consume and second in terms of the availability of credit in recessions.

The organisation of this chapter is as follows: in section 2.2 I discuss the context of the KS model and other additions to it that have previously attempted to improve its empirical realism. In section 2.3 I outline the major features of the KS model and discuss a commonly used method to solve it. Next, in section 2.4 I discuss the model's results in contrast to representative agent models. Section 2.5 shows the benchmark model's wealth distribution versus empirical distribution calibrated to the pre-recession and recession period data. Next, in section 2.6 I show the characteristics of the benchmark model by adjusting key parameters. In 2.7 I discuss how to add heterogeneous discount factors to the model. I discuss the contradictions of this addition in section 2.8 and conclude in section 2.9.

2.2 Related Literature

The Krusell and Smith (1999) model sits within a class of models known as Bewley models, from Bewley (1979), in which agents face idiosyncratic earning shocks that they can only partially insure themselves from. Other important Bewley models include Aiyagari (1994) and Huggett (1993); in section 2.4.1 below I discuss these types of models and establish the link to a representative agent Ramsey (1928) model.

A a well-discussed feature of the KS model is that, without modification, it does a poor job of fitting empirical wealth distributions. Indeed, Krusell and Smith (1998) note this themselves. There have been a multitude of extensions to the model which attempt to fix its lack of empirical realism. One method is including life cycle effects, so that in addition to a precautionary motive for saving, agents also save for retirement or ill-health. Models also change the degree of market incompleteness in the economic environment, such as unemployment insurance and other government programmes.[17] These different additions have had mixed success. Krueger et al. (2016) finds that the addition of life-cycle effects has minimal effects on the wealth distribution. They also find that additions which reduce the degree of insurance over income variability, or add idiosyncratic labour productivity risk, generate larger declines in aggregate consumption than the benchmark KS model. However, Huggett (1993) finds that such modifications imply an amount of wealth held by the poorest agents which is too low. Carroll et al. (2017) adds permanent income shocks to the model, but finds that this does not greatly improve the model's fit. There is a large literature on heterogeneous rates of return, including Cagetti and De Nardi (2006) and Quadrini (2000) which include entrepreneurs as well as workers, which can better represent the large tail at the top of the wealth distribution.

The focus of this chapter is on another often-used method for fitting the cross-sectional wealth distribtion: dispersion in patience. This has been used in Krusell and Smith (1998), Krueger et al. (2016), Carroll et al. (2017) and Castañeda et al. (2003) among others. It is generally accepted as a relatively straightforward way to capture the features of inequality across the entire distribution. My contribution is to focus not on the cross-sectional performance of this model, but rather the dynamics of the wealth distribution over the cycle. In doing show I show that the model exhibits fundamental contradictions.

[17] Excellent reviews of this literature include Guvenen (2011) and Heathcote et al. (2009).

2.3 The Krusell Smith Model

KS consider an economy in which there is a continuum of infinitely-lived agents of measure one. Time is discrete, $t = (0, 1, 2, ...)$ and each agent has preferences over flows of consuming the single consumption good, c, that can be described by:

$$\sum_{t=0}^{\infty} \beta^t U(c_t)$$

with constant relative risk aversion (CRRA) utility:

$$U(c) = \lim_{i \to \sigma} \frac{c^{1-i} - 1}{1 - i}$$

Because leisure is not valued, agents spend all of their time - each is endowed with one unit - working when employed. Idiosyncratic risk is introduced through a stochastic shock to labour input:

$$e_i \in E = \begin{cases} 1 & \text{for } i = g, \text{ 'employed';} \\ 0 & \text{for } i = b, \text{ 'unemployed'.} \end{cases}$$

Aggregate labour L combines with aggregate capital K to make production good Y according to the Cobb-Douglas production function $Y = zK^{\alpha}L^{1-\alpha}$ where $\alpha \in [0, 1]$ and z is the aggregate state of the economy, which feeds through the model as a shock which can take two values:

$$z_i \in Z = \begin{cases} 1 + \delta_z & \text{for } i = g, \text{ 'expansion';} \\ 1 - \delta_z & \text{for } i = b, \text{ 'recession'.} \end{cases}$$

Where δ_z is a calibration parameter. KS assume that the aggregate state, z and the idiosyncratic shock e follow a first order Markov process with the transition matrices π_z and $\pi_{e,e'|z,z'}$, respectively. Following standard notation a prime signifies the next period's realisation, so that $\pi_{z,z'}$ is the probability that the aggregate state transitions to z' next period from this period's realisation is z. $\pi_{e',z'|e,z}$ is the probability that next period's idiosyncratic shock is e' and that the aggregate shock is z' given that this period's employment realisation is e and the aggregate shock is z. There are no markets for insurance against uncertainty, so agents may only undertake a form of self-insurance by investing in a single asset, capital, which is restricted to take values $k \in \kappa = [0, \infty)$.

Individual Agent's Problem An individual agent's optimisation problem is the following:

$$V(k, e, z, \Gamma) = \max_{c \in \mathbb{R}^+,\, k' \in \kappa} \left\{ U(c) + \beta \sum_{z' \in Z} \sum_{e' \in E} \pi_{e'z'|e,z} V(k', e', z', \Gamma') \right\} \tag{2.8a}$$

subject to:

$$k(1 + r(K, L, z) - \delta) + [(1 - \tau)\bar{l}e + \mu(1 - e)]w(K, L, z) - c = k' \tag{2.8b}$$

$$\Gamma' = G(\Gamma, z, z') \tag{2.8c}$$

$$k' \geq 0. \tag{2.8d}$$

Where $r(\cdot)$ is the real interest rate and $w(\cdot)$ the wage rate, δ is the constant rate at which capital depreciates, $\bar{l}$ is individual time endowment, μ unemployment insurance as a percentage of the wage rate, τ is a tax on labour income and Γ the measure of agents over wealth and employment status. Equation 2.8a is a standard Bellman equation. Budget constraint (2.8b) states that the future individual capital stock is composed of today's capital, compounded by the depreciation-adjusted rental price of capital, $r(K, L, z) - \delta$, the labour income $(1 - \tau)\bar{l}w(K, L, z)$ when an agent is employed, or $\mu w(K, L, z)$ if an agent is unemployed, less today's consumption. (2.8c) is the forecasting rule for the future distribution of Γ and for the aggregate state variable. Agents about the next period's distribution because it determines future prices. Finally, (2.8d) is the borrowing constraint: which restricts next period's capital choice to be positive.

Government The only role of government in the model is to tax labour income to fund the payment of unemployment insurance, they run a balanced budget each period. This means that:

$$\underbrace{w(K, L, z)\tau\bar{l}L}_{\text{government income}} = \underbrace{w(K, L, z)\mu(1 - L)}_{\text{government expenditure}}$$

which implies that the tax rate is:

$$\tau = \frac{\mu(1 - L)}{\bar{l}L}$$

where L is total employed labour, and $(1-L)$ the unemployment rate.

Firm's Problem Factor prices follow from the competitive firm's optimisation problem, as in the standard representative agent model:

$\text{MPL} = \frac{\partial Y}{\partial L} = (1-\alpha)z(K/L)^{\alpha} = w(K,L,z)$;
$\text{MPK} = \frac{\partial Y}{\partial K} = \alpha z(K/L)^{\alpha-1} = r(K,L,z)$, where the last equalities hold due to competitive markets, and where:

$$K = \int_A k' \quad d\Gamma \tag{2.9}$$

$$L = \int_A e \quad d\Gamma. \tag{2.10}$$

where $A = \kappa \times E$ is the type space of agents over capital holdings and employment status. The associated measurable space is $M = (A, \mathcal{B}(A))$ where $\mathcal{B}(A) = \mathcal{B}(\kappa) \times \mathcal{P}(E)$ is the Borel σ-algebra of A and $\mathcal{P}(E)$ is the power set of E. The set of all measures on M is $\mathcal{M}$, and we shall require that Γ is an element of $\mathcal{M}$.

2.3.1 Recursive Competitive Rational Expectations Equilibrium

The KS recursive competitive equilibrium can be defined in the following way:

Definition 1. Recursive competitive rational expectations equilibrium
A recursive competitive rational expectations equilibrium consists of:
(i) A value function: $V^*(k,e,z,\Gamma) : A \times Z \times \mathcal{M} \to \mathbb{R}$ which solves the individual's optimisation problem (2.8a), with the associated optimal decision rule for capital:
$g_{k'}(k,e,z,\Gamma) : A \times Z \times \mathcal{M} \to \mathbb{R},\ g_{k'}(k,e,z,\Gamma) = k'^*$
(ii) Pricing functions:
$w^*(K,L,z) : \mathcal{M} \times Z \to \mathbb{R},\ w^*(K,L,z) = (1-\alpha)z(K/L)^{\alpha}$
$r^*(K,L,z) : \mathcal{M} \times Z \to \mathbb{R},\ r^*(K,L,z) = \alpha z(K/L)^{\alpha-1}$
which solve the firm's optimisation problem.
(iii) An equilibrium transition function:
$G^*(\Gamma,z,z') : Z \times Z \times \mathcal{M} \to \mathcal{M},\ G^*(\Gamma,z,z') = \Gamma'$
that is consistent with the law of motion for Γ implied by individual decision rule, $g_{k'}(\cdot)$, and the Markov process $\pi_{e',z'|e,z}$.

2.3.2 Computational Strategy

The recursive competitive rational expectations equilibrium is not solvable analytically due to the nature of the equilibrium function G^*, which is a doubly-infinite-dimensional operator. KS use two approximating steps to reduce the state space. The first is to make some restrictions on the Markov process so that the unemployment rate is constant (but different) for each z. This has the effect of reducing the number of state variables, and so we only need to keep track of agents' holdings of capital, $\tilde{\Gamma}$. However, the law of motion for capital holdings $\tilde{G}$ still maps an infinite dimensional object to itself. So the second simplification is to propose using a finite sub-sample of the moments of $\tilde{\Gamma}$ to forecast the entire future distribution.

The algorithm takes the form of an inner and outer loop.[18] In the outer loop, we specify the functional form and coefficients of a forecasting function which some subset of information of the entire wealth distribution $l_j(\tilde{\Gamma})$ where j is the number of statistics of the distribution used. This information is updated using the forecasting function $G_j(l_j, z)$. Given $\{G_j, l_j\}$ we solve the individual problem to get $g_{k'}(k, e, z; G_j, l_j)$. We then initialise a large sample of agents of dimension N with initial values of $\{k_i^0, e_i^0\}_{i=1}^N$ from which we compute $l_j(\tilde{\Gamma}^0)$. Using the Markov transition matrix and individual policy $g_{k'}$ we then update $\{k_i^1, e_i^1\}_{i=1}^N$. The algorithm continues in this fashion until some predetermined simulation end point T, when we run a set of linear regressions and check for correspondence between the coefficients of $\hat{G}_j$ and G_j, call them $\hat{b_j}$ and b_j, respectively. If the two are within some error ϵ of each other, we say that the solution has been reached and the algorithm solves for prices, if not then we update the regression coefficients of G_j as $\tilde{b_j} = \lambda b_j + (1 - \lambda)\hat{b_j}$ where λ is a smoothing parameter. For example, if $j = 1$ then we may specify the functional form of the forecasting function as $G_{K,z} = \log(K') = \phi_{K,z;0} + \phi_{K,z,1} \log K$. Once the simulation is run, we compare estimates $\widehat{\phi_{K,z;0}}$ and $\widehat{\phi_{K,z;1}}$ with $\phi'_{0,z}$ and $\phi'_{1,z}$ and iterate until the coefficients of the forecasting equation at the individual level are consistent with the parameters at the aggregate level.

So there is some mapping Φ from the perceived law of motion G to the actual law of motion $G^* = \Phi(G)$ and we want to find the fixed point $G = \Phi(G)$. The major difficulty in using this algorithm is that Φ is not a contraction - so a good initial guess is vital. The key finding of the Krusell and Smith (1999) paper was to show that simply using the mean of the capital distribution is an adequate statistic for agents

[18] Here I present the intuition for the algorithm. See appendix B.1 for a more rigorous treatment.

to use in order to forecast the entire distribution to a high degree of accuracy. This finding is termed *approximate aggregation*, so a suitable initial guess is the steady state solution to corresponding representative agent problem, a link which I will develop in the following section.

2.4 Approximate Aggregation

2.4.1 Link with representative agent models

To see why approximate aggregation holds, consider the following simple example. Without individual or aggregate uncertainty in the KS model, if agents had linear saving policies, each individual i having the same intercept ϕ_0 and constant marginal propensity to save ϕ_1, the individual policy function would take the form:

$$k_i' = \phi_0 + \phi_1 k_i$$

Then aggregation is easy:

$$K' = \phi_0 + \phi_1 K.$$

Because we are working with probability space and normalise total labour supply, L to be one, the first moment is equal to total asset holding, K. We can *exactly* aggregate all of the individual policy functions and the first moment of the wealth distribution is a the only statistic we need to perfectly forecast capital stock tomorrow.

Approximate aggregation holds in the KS model because the vast majority of agents act approximately in this manner, having near-linear savings functions and constant marginal propensities to save. Only a few that are constrained have very low zero marginal propensity to save out of income, but they are too small in number to affect the aggregate result dramatically. Figure (2.8) plots the individual capital policy functions for the baseline KS economy. Though functions exhibits non-linearity for the poorest agents, there are very few agents in this region, and low amounts of redistribution to this area.

Figure 2.9 shows the diagrammatic representation of competitive equilibrium in a textbook representative agent model. Specifically, it is the steady state of the Ramsey model (Ramsey, 1928), a model which features a single representative agent and no aggregate uncertainty. The capital demand curve K^D comes directly from the firms'

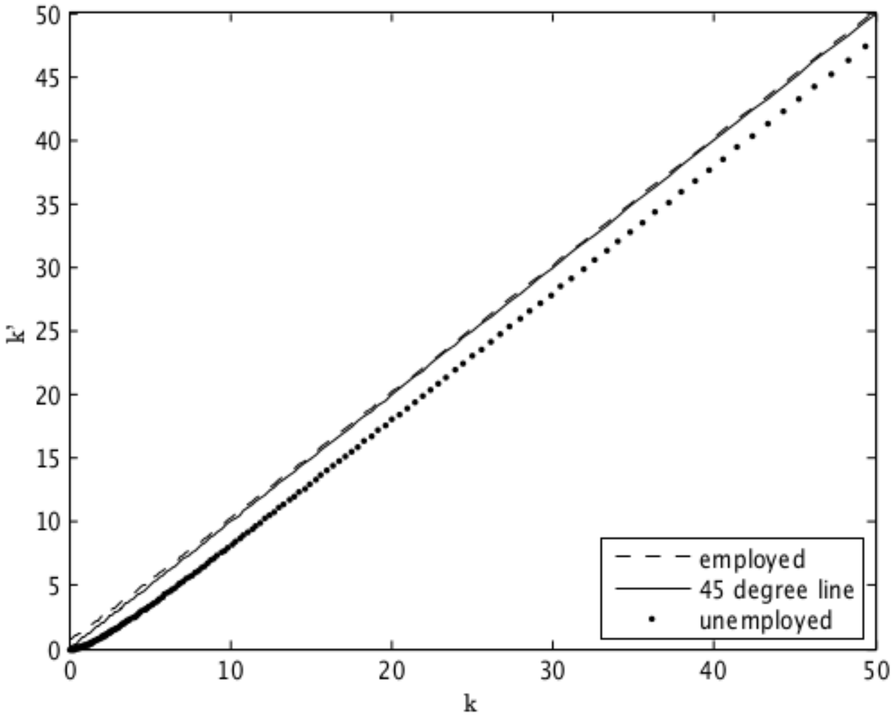


Fig. 2.8 Individual Capital Policy Functions in the KS Model

This period's individual capital (k) plotted against next period's capital choice (k') for aggregate capital=39 and good aggregate state.

maximisation problem, and equals the marginal product of capital (MPK). The capital supply curve K^S is clearly defined by the representative agent's maximisation problem, capital is supplied inelastically such that the impatience of households exactly equals the rewards of patience so that $r = \rho$. We can see from the diagram that the equilibrium of this model e^R exists at the intersection of the two curves; the equilibrium is unique and stable. The intuition behind this result is that if the economy starts from a low capital base, capital has a high marginal product. This induces the representative agent to save more as a proportion of income. As a result aggregate saving is greater than that which is required to replace the depreciating capital stock, therefore its intensity increases. As this happens, a decreasing marginal product of capital induces saving to decline until eventually it is just sufficient to maintain the capital intensity. A similar argument can be made for an economy starting with a high level of capital. Because the interest rate and rate of time preference are perfectly balanced, capital does not grow over time: corresponding to an aggregate law of motion where $\phi_0 = 0$ and $\phi_1 = 1$.

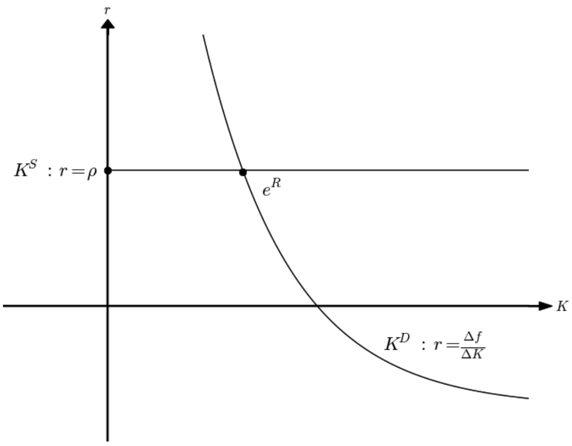


Fig. 2.9 Steady State in the Ramsey Model

The capital demand curve K^D comes from the firm's maximisation problem, they equate the marginal product of capital $\frac{\Delta f}{\Delta K}$ with its marginal cost r. The capital supply curve K^S comes from the representative agent's problem, they equate the gain from saving r with their level of impatience ρ.

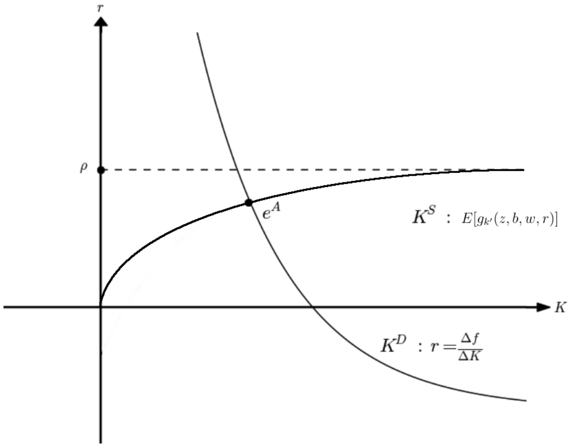


Fig. 2.10 Steady State in the Aiyagari Model

The capital demand curve K^D is determined as in the representative agent model. The capital supply curve K^S is given by expected long run average assets, with the expectation taken with respect to the stationary distribution of z. This figure assumes a borrowing constraint, b equal to 0.

While the capital demand curve in the KS model is determined in exactly the same way as in the representative agent model, the capital supply curve is not analogous, indeed it is not well-defined at all. To see this consider a model which, conceptually, is a step between the representative agent model just discussed and the KS model.

The Aiyagari (1994) model, like KS, features agents which become endogenously heterogeneous. Furthermore, idiosyncratic uncertainty and a borrowing constraint also generate a precautionary motive for saving. Unlike the KS model, Aiyagari abstracts from aggregate uncertainty in order to focus on the steady state equilibrium where the type distribution of agents, and therefore prices, is constant over time. This steady state equilibrium is shown in figure 2.10. Capital demand is determined in the same fashion as the Ramsey and KS models. The capital supply curve is more interesting than the representative agent case, in that it is an increasing function of the interest rate. This occurs because of the different histories of labour endowment shocks to agents. Some agents are unlucky: their filtration involves more negative shocks than others. They will want to use their savings to smooth consumption. However, they do not wish to consume all of their savings as the poorer they get the closer they get to the borrowing constraint, and so the greater the likelihood of violating their Euler equation. This trade-off illustrates why the capital supply curve is upward sloping. It also explains why the borrowing constraint generates a precautionary savings motive.

Clearly, the equilibrium only exists for $r < \rho$ since demand for assets goes off to infinity for values close to, or exceeding ρ. This steady state is then determined where capital demand is equal to capital supply, at a lower interest rate and with higher saving levels than in the representative agent equilibrium.

The KS model is the Aiyagari model with aggregate shocks to the economy, where the type distribution of agents changes over time. This can intuitively be thought of as e^A moving with the aggregate state in figure 2.10. This also illustrates why agents must keep track of the distribution of capital, since this affects aggregate capital and forecasts the interest rate r. The more nonlinear the individual capital policy functions, and the greater the mass of individuals in the nonlinear part of the policy functions, the greater the response in aggregate capital in response to aggregate shocks.

2.5 Benchmark KS model vs. Data

In this section, I take the KS model to the data and briefly reiterate the well-known fact that, in its benchmark form, it cannot capture the degree of wealth inequality seen in US PSID data. I then detail how the commonly used method of dispersion in discount factors helps to fit the cross-sectional wealth distribution with much greater accuracy. Finally, I show that this technique implies a contradiction when the model is calibrated to the data over the Great Recession.

Figures 2.11 and 2.12 compare the wealth distributions generated by the KS benchmark calibration for good and bad aggregate states with the empirical wealth distributions in 2006 and 2008. Clearly, there are major shortcomings in matching the distribution. In the cross section, the empirical distribution features a mass of families around the zero wealth mark, a heavily right-skewed distribution and a significant number of families with negative wealth. The KS distribution is also right-skewed, but not nearly to the same extent, with a much smaller range of wealth values. Furthermore, no agents have zero wealth or negative wealth. In terms of the dynamics, we see that empirically many more families had zero or negative wealth in 2008 than in 2006, whereas the KS distribution features a leftward shift of the distribution but again features no agents with zero or negative wealth.

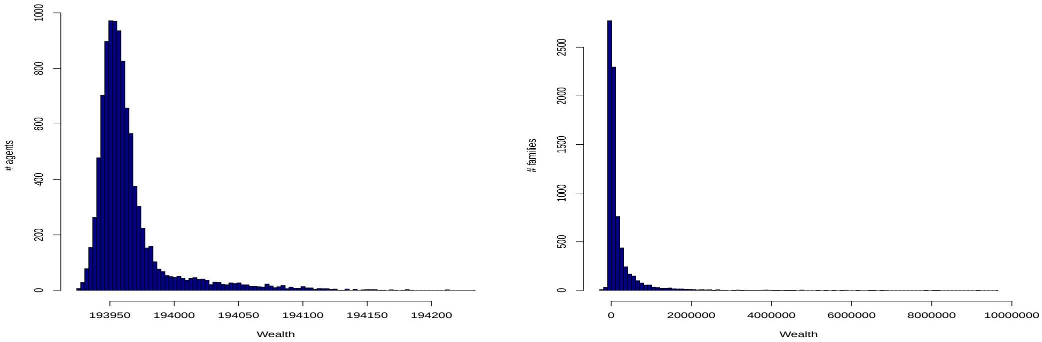


Fig. 2.11 Benchmark KS model wealth distribution (left) versus data (right), good aggregate state

Benchmark calibration of the KS model in the good aggregate state (left) scaled to make aggregate capital K equal to the mean of the empirical wealth distribution in 2006 (right).

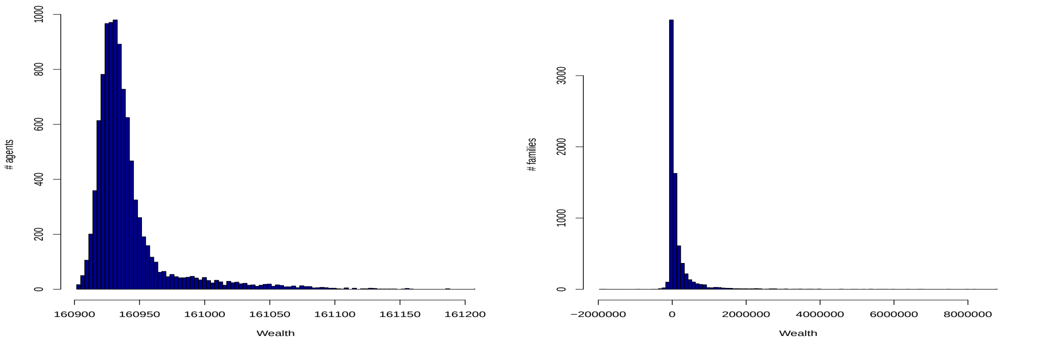


Fig. 2.12 Benchmark KS model wealth distribution (left) versus data (right), bad aggregate state

Benchmark calibration of the KS model in the bad aggregate state (left) scaled to make aggregate capital K equal to the mean of the empirical wealth distribution in 2008 (right).

2.6 Changing the Parameters of the KS Model

Table 2.2 shows the effects on aggregate capital of experimenting with key parameters of the model. The full list of parameters in the baseline KS model is reported in table 2.1. I report aggregate capital as this summarises the combined effect of more mass in the nonlinear region of the policy rule (agents face more bad luck) and a more nonlinear policy function (the precautionary savings motive is higher).

Table 2.1 KS Baseline Parameters

Parameter	Description	Value
α	Elasticity of Output w.r.t. Capital	0.36
β	Discount Rate	0.99
δ	Depreciation Rate	0.025
σ	Elasticity of Intertemporal Substitution	$1^{\dagger}$
ϕ	Borrowing Constraint	0
μ	Unemployment Insurance (Replacement Rate)	0.15
$\bar{l}$	Individual Time Endowment	1
δ_z	Size of the Aggregate Shock	0.01
ψ	Recession multiplier‡	1.25

Aggregate State

	z_g	z_b
Unemployment duration	$1.5Q^*$	2.5 Q
Unemployment rate	0.04	0.1
Duration of aggregate state	8 Q	8 Q

Markov Transition Matrix

$e, z \backslash e'z'$	$\{e'_g, z'_g\}$	$\{e'_g, z'_b\}$	$\{e'_b, z'_g\}$	$\{e'_b, z'_b\}$
$\{e_g, z_g\}$	0.850694	0.583333	0.122917	0.09375
$\{e_g, z_b\}$	0.024306	0.291667	0.002083	0.046
$\{e_b, z_g\}$	0.115885	0.03125	0.836111	0.096
$\{e_b, z_b\}$	0.009115	0.563	0.023	0.525

Notes:

† Implies logarithmic utility.

‡ The probability of remaining unemployed when economy transitions from $z = z_g$ to $z' = z_b$ is ψ times the probability of remaining unemployed when economy transitions from $z = z_b$ to $z' = z_b$.

* Quarters.

Table 2.2 Experiment Model Parameters

Parameter	Description	KS Values			Experimental Values		
		Value	$\bar{K}^{bad}$	$\bar{K}^{good}$	Value	$\bar{K}^{bad}$	$\bar{K}^{good}$
δ_z	Size of the aggregate shock	0.01	39.07	39.65	0.2	38.73	40.07
μ	Unemployment insurance (replacement rate)	0.15	"	"	0	39.16	39.73
σ	Risk aversion	1†	"	"	0.4	39.01	39.55
β	Discount factor	0.99	"	"	0.98	39.15	39.65

Notes: † Implies logarithmic utility. Aggregate capital K in the good and bad aggregate state for the KS model benchmark parameters and experimental values listed.

Changing the size of δ_z determines the size of the productivity shocks to the aggregate economy. This primarily affects the division of output rather than the total amount of output, as in an expansion (recession) there is more (less) income to be distributed to the factors of production. Looking at table 2.2 reveals that even pushing δ_z up to 0.2, i.e., 20% of output lost in a recession - 4 times greater than the Great Recession - only serves to push aggregate savings in the bad aggregate state down slightly, and up slightly in the good aggregate state. It doesn't greatly affect the cross sectional inequality or dynamics of the wealth distribution due to the infinite horizon nature of the model: the effective time period is so long that the ability to self-insure against shocks is very high.

Table 2.2 also details some of the results of lowering σ. This has the effect of making agents less risk averse, inducing agents to save less, and induces slightly greater non-linearities in the capital policy by making it more likely that they are close to the borrowing constraint. Overall, reducing σ significantly has a very minimal effect on the wealth distribution, individual capital policy functions, and aggregate capital.

The idea behind changing μ, the replacement rate, to zero is to not offer agents a safety net when unemployed: this should increase idiosyncratic risk, and increase the number of 'hand-to-mouth' consumers. Here my results are consistent with Krueger et al. (2016): very little about the aggregate dynamics, individual policy functions and wealth distribution changes even when we dispose of this safety net entirely.

The final experiment in table 2.2 lowers β from a value of 0.99 to 0.98. From these results it is clear to see why modifying the discount factor has been a popular modelling choice: lowering this rate by only 0.01 increases aggregate capital in the bad aggregate state by as much as removing unemployment benefits entirely. In the following section I show the results of extending this simple experiment to have a distribution of βs in order to capture the empirical wealth distribution.

2.7 Improving the distributional fit (β-Dist)

Improving the fit to the wealth distribution goes back to Krusell and Smith (1998) in which they added the assumption of a stochastic discount factor, $\tilde{\beta}$, which can take values $\{0.9858, 0.9894, 0.9930\}$. $\tilde{\beta}$ follows a three-state Markov chain which generates an invariant distribution for discount factors that is symmetric around its mean. KS gave the intuition that this was a way of modelling overlapping generations with different levels of patience - it in fact creates three types of agents (impatient, baseline, patient). I use the specification from Castañeda et al. (2003) because it is much quicker to solve, and so is more often used in the literature. The major difference between this and the stochastic discount factor model is that agents' discount parameters do not change over time, as such the model generates much less mobility in the wealth distribution. Specifically, they choose time preference parameters to be distributed uniformly in the population between $\grave{\beta} \pm \nabla$ to fit the proportion of wealth w held by richest 20,40, 60 and 80%, ie:

$$\{\grave{\beta}, \nabla\} = \underset{\beta,\nabla}{\operatorname{argmin}} \left(\sum_{i=20,40,60,80} (w_i(\beta, \nabla) - w_i)^2 \right)^{1/2} \tag{2.11}$$

Using a distribution of discount factors helps to better fit the skewness of the empirical distribution as it attenuates the precautionary saving motive for agents with lower discount factors to generate a larger mass at the bottom end of the distribution. In a sense, they become myopic to likelihood of hitting the borrowing constraint. It also fits the upper parts of the distribution by heightening the desire to save for agents with higher discount factors. It is not only a useful device for better fitting the empirical distribution, but also backed by empirical evidence of heterogeneity in discount factors. In a study of military drawdown payments, Warner and Pleeter (2001) find discount factors between 0.76 and 1.0 when military personnel were given the choice between a lump-sum payment or annuity. In order to best fit the minimisation problem of equation 2.11, I find that a much smaller variation in $\grave{\beta}$ of $\nabla = 0.01$ is sufficient to fit the empirical distribution. This much smaller variance is likely due to coarse fitting points, in accordance with the literature I use only 4 datapoints and do not fit the maximum or minimum (0 % or 100 %) quantiles.[19] Furthermore, Warner and Pleeter (2001) find that individual discount factors depend on the amount of money under consideration. Their study deals with large lump-sum or annuity payments, whereas the individuals in this study face ongoing savings considerations of variable amounts.

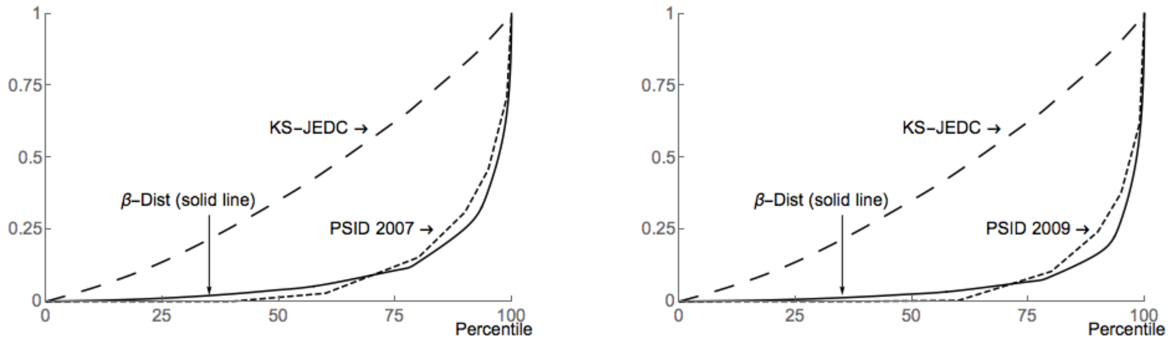


Fig. 2.13 Distribution of Wealth (Lorenz Curves)

Wealth distributions for Krussell-Smith (KS-JEDC) vs. β distribution, calibrated to 2006 (left) and 2008 (right) PSID data.

Figure 2.13 shows Lorenz Curves generated from solving for the $\grave{\beta}$s and ∇s which solve equation 2.11 for PSID waves 2007 (capturing 2006 data, i.e., pre-recession) and 2009 (2008 recession data). The dashed line labelled KS-JEDC is the benchmark KS model. The solid line labelled β-Dist is the KS model with the addition of heterogeneous discount factors.Clearly, a relatively small variation in discount factors can dramatically improve the fit to the empirical wealth distribution. The baseline KS model exhibits very little wealth inequality while the β-Dist models capture the pre-recession and recession data closely. Table 2.3 shows how this addition to the model accomplishes this: by creating much greater variation in the marginal propensity to consume over the cross section. In the 2007 calibration, the poorest agents[20] consume over 30% of a shock to income, this figure decreases as income levels increase, with the richest consuming 15%. High MPCs are concentrated in unemployed agents, who consume

[19] To fit the distribution more closely is a small modification to the algorithm. The contradiction in business cycle dynamics still exists in this case.

[20] I report the MPCs for annual income quintile, a very similar pattern of dispersion exists when looking in terms of wealth quintiles.

nearly 60% of an income shock in the 2007 calibration, compared to just over 20% for employed agents. In the 2009 calibration, the dispersion in marginal propensity to consume is much greater. The poorest agents consume over 50% of a shock to income, with the richest increasing their share to 25%. Both employed and unemployed agents increase their MPC compared to the 2007 calibration by around 10 percentage points, with unemployed agents consuming over 70% of an income shock.

Table 2.3 Marginal Propensity to Consume over the Business Cycle - 2006 and 2008 Calibrations Compared

	Krusell–Smith (KS): β-Dist							
Model	2007 Calibration				2009 Calibration			
Scenario	Baseline	Recession	Expansion		Baseline	Recession	Expansion	
Overall average	0.25	0.27	0.24		0.35	0.37	0.33	
By Income Quintile								
Q1	0.33	0.39	0.26		0.51	0.58	0.43	
Q2	0.2	0.2	0.2		0.34	0.34	0.33	
Q3	0.2	0.21	0.2		0.32	0.33	0.32	
Q4	0.19	0.19	0.18		0.3	0.3	0.29	
Q5	0.15	0.16	0.15		0.25	0.26	0.24	
By employment status								
Employed	0.22	0.23	0.22		0.31	0.31	0.31	
Unemployed	0.58	0.6	0.56		0.73	0.74	0.72	
Time preference parameters‡								
$\grave{\beta}$		0.9837				0.9787		
∇		0.0108				0.0172		
PSID 2007 % of wealth held by the richest:	20%	40%	60%	80%				
	80.6	95.1	99.9	100.8				
PSID 2009 % of wealth held by the richest:					20%	40%	60%	80%
					85.5	97.3	100.8	101.3

Notes: Annual MPC is calculated by $1-(1-\text{quarterly MPC})^4$. The scenarios are calculated for the β-Dist models calibrated to the net worth distributions described. For the KS aggregate shocks, the results are obtained by running the simulation over 1,000 periods, and the scenarios are defined as 'Recessions/Expansions': bad/good realization of the aggregate state. ‡: Discount factors are uniformly distributed over the interval $[\grave{\beta}-\nabla, \grave{\beta}+\nabla]$.

2.8 Contradictions in the β-Dist model

2.8.1 Dynamics of the MPC

Table 2.3 also shows a contradiction of the model including heterogeneous discount factors. When looking the dispersion of the MPC across the distribution's internal business cycle dynamics (comparing columns 'Recession' and 'Expansion' within a calibration), it is clear to see that in both the 2007 and 2009 calibrations, the MPCs vary very little over the cycle. In the 2007 calibration, the aggregate marginal propensity to consume increases from 0.25 to 0.27 in a recession, and falls to 0.24 in an expansion. Similarly, the 2009 calibration increases from an MPC of 0.35 to 0.37 in a recession and falls to 0.33 in an expansion. However, the implied difference in MPC given the wealth distributions *accross* the calibrations are 10 percentage points higher in the recession sample than the pre-recession sample. To make this point more clearly, figure 2.14 plots these MPC values within calibrations (top two figures) and across calibrations (bottom figure). While a recession increases the MPC for the very poorest quintile significantly, the rest of the distribution barely changes. In contrast, to fit the wealth distributions across the calibrations requires a shift in the MPCs, and therefore individual policy functions, for the whole of the distribution. The within-calibration MPC changes are consistent with a greater mass of agents becoming closer to the borrowing constraint. The across-calibration MPCs suggests that preferences across the distribution have fundamentally changed, or something else has occurred in the Great Recession to shift individual policy functions that the model is not capturing.[21]

[21]Note that these results are obtained without making any special assumptions about the nature of the Great Recession in terms of its severity or duration. Krueger et al. (2016) explores calibrating the KS model aggregate shocks to the frequency of observed severe recessions - defined as historical periods where unemployment exceeded 9% for at least one quarter and remains above 7% thereafter. Employing such a calibration does not change the qualitative contradiction in the results.

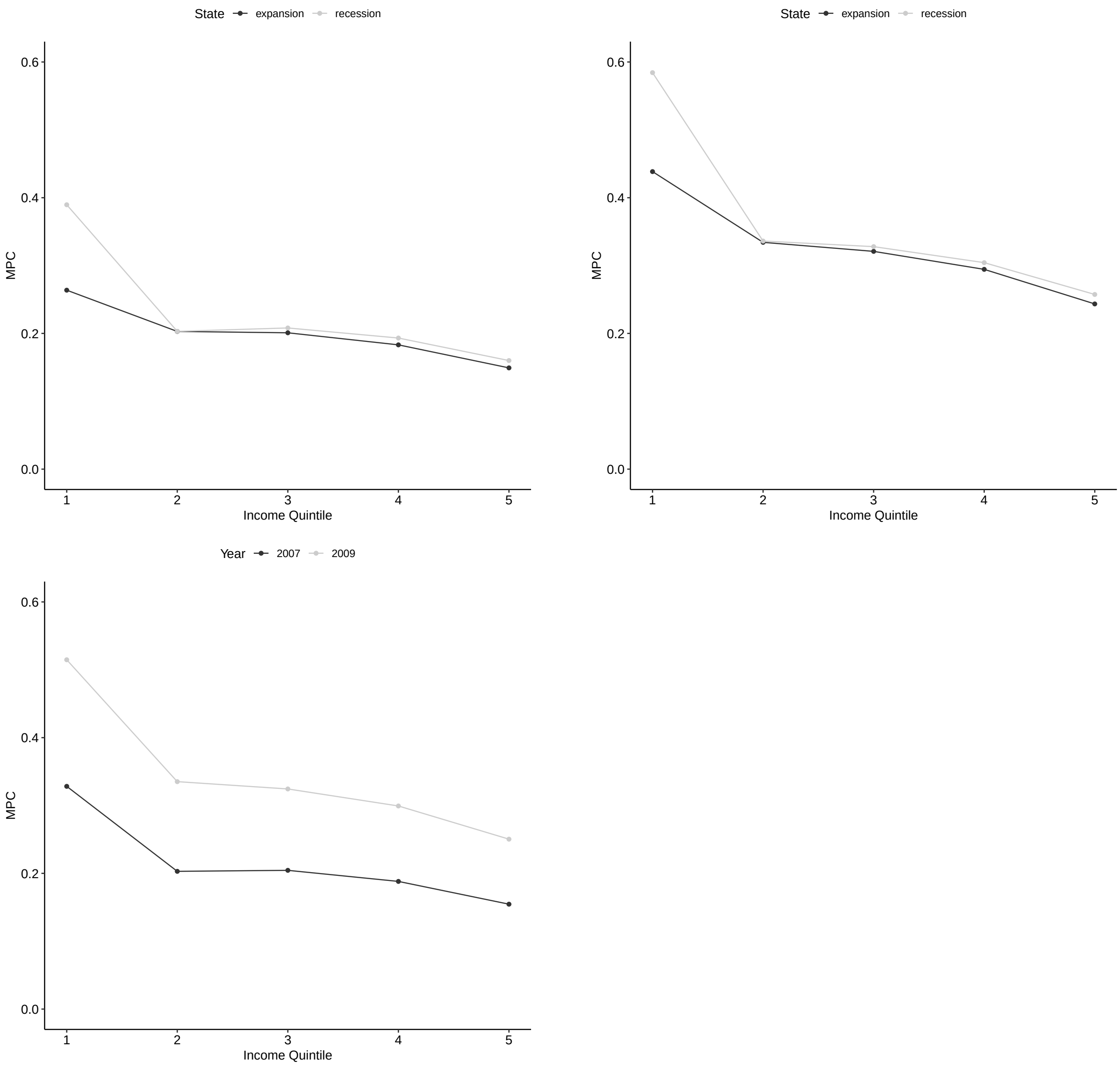


Fig. 2.14 KS β-Dist Simulated MPC at the Income Quintiles

MPC at the income quintiles generated from 2006 calibration pre-recession (top left) and 2008 calibration in expansion (top right). Compared with baseline 2006 and baseline 2008 calibrations (bottom left). Annual MPC is calculated by $1-(1-\text{quarterly MPC})^4$. Calculated for the β-Dist models calibrated to the net worth distribution for a given year. The results are obtained by running the simulation over 1,000 periods. Recession/Expansion MPCs are defined as averaging over bad/good realizations of the aggregate state. Baseline MPCs are defined as averaging over all realizations of the aggregate state.

2.8.2 Borrowing constraint

I consider a second modification to the benchmark KS model which implies a contradiction when compared to PSID data. This modification to the benchmark model is the lowering of the borrowing constraint. To my knowledge, no other paper has considered this modification - probably because it is trivial - in terms of the solution it simply shifts the distribution by a constant and has no effects on the dynamics.[22] However, I consider it firstly because a significant proportion of individuals in the PSID hold zero or negative net wealth: 12.7% in 2006, 16.1% in 2008. Secondly, I will show that changing the borrowing constraint implies a contradiction with empirical evidence that finds that credit constraints are higher in recessions than in normal economic times.[23] To fit the evidence of significant holdings of zero or negative wealth, I add an outer loop to the algorithm which solves the model, which uses the 2006 β-Dist calibration and lowers the budget constraint by 0.1 until the gap between the model-generated percentage of agents holding negative wealth is within $\epsilon = 0.01$ of the 2006 empirical figure. Because the algorithm fits the percentage of people with negative wealth, rather than the cumulative wealth held, it doesn't do a great job of improving the fit of the empirical Lorenz Curves - compare figures 2.15, the empirical Lorenz curve estimated from the PSID and the KS β-Dist model generated 2.16. In the data, both the fraction of individuals holding negative wealth and the amounts of negative wealth increase substantially in the recession relative to the pre-recession estimation. Figure 2.16 shows the Lorenz curve in the good and bad aggregate state within the 2007 calibration; neither the fraction of agents holding negative wealth nor the amounts of negative wealth held change significantly in the dynamics over the cycle (which should not be surprising, given that this modification does not change the dynamics of the β-Dist model).

[22] Not to mention, it takes a long time to solve - one iteration of the Carroll et al. (2017) Mathematica code takes around 8 hours on my MacBook Pro 2013 laptop with 2.6 GHz processor and 8 GB RAM; I rewrote the algorithm based on Maliar et al. (2010) (see Appendix section B.2.1) code in Matlab R2016b to get a total running time of 24 hours for all iterations of the borrowing constraint.

[23] Chapter 3 provides an overview of this evidence.

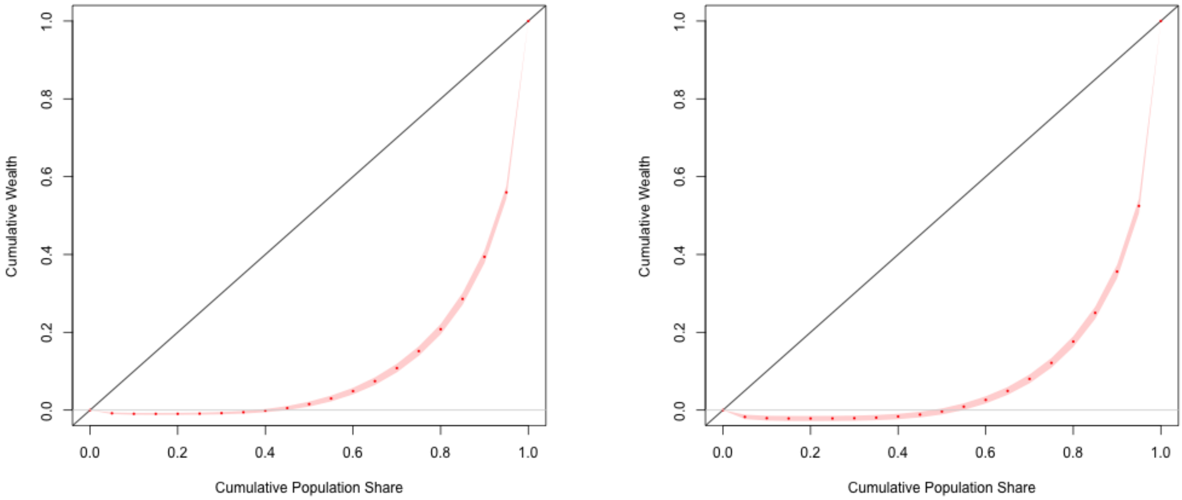


Fig. 2.15 Empirical distribution of Wealth (Lorenz Curves)

Lorenz curves estimated from the PSID 2007 (left) and 2009 (right). Red bands are survey-weighted confidence intervals.

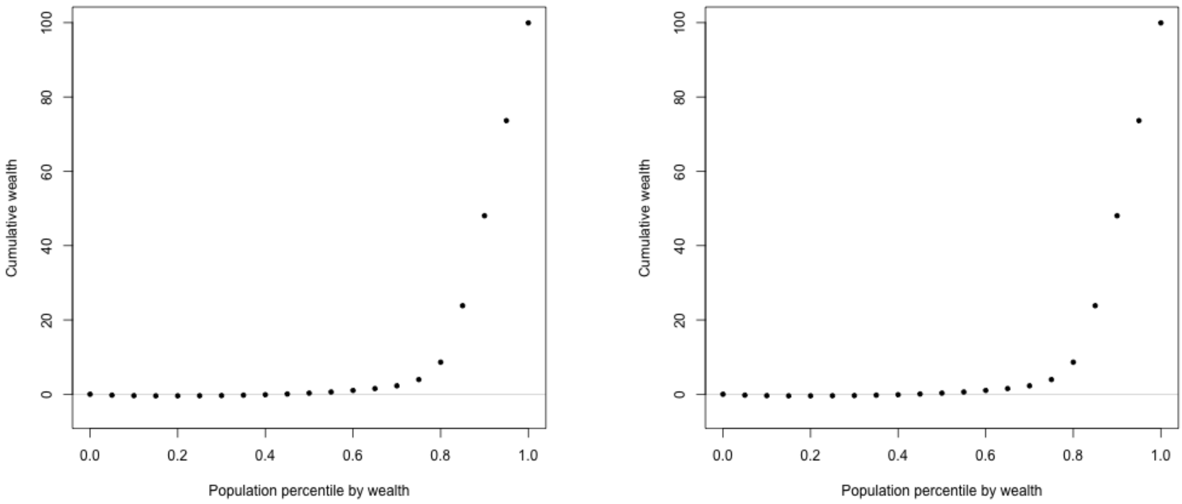


Fig. 2.16 KS β-Dist Simulated Lorenz Curves

Lorenz curves generated from 2006 calibration with BC=-3.3 in good aggregate state (left) and bad aggregate state (right).

What is surprising is the implications for the borrowing constraint over the cycle. I find that the borrowing constraint that fits the percentage of negative wealth holdings in 2006 is -3.3. Figure 2.17 plots the percentage of the population holding negative wealth for the β-Dist model solved with progressively looser borrowing constraints, lowered by 0.1 on each iteration. The relationship between the fraction holding negative wealth and the borrowing constraint is positive and convex. This implies that, in order to better fit the greater mass of agents holding zero or negative wealth in the 2008 recession, it implies that the borrowing constraint has to be *looser*, i.e. that agents can borrow more, not less, in a recession.

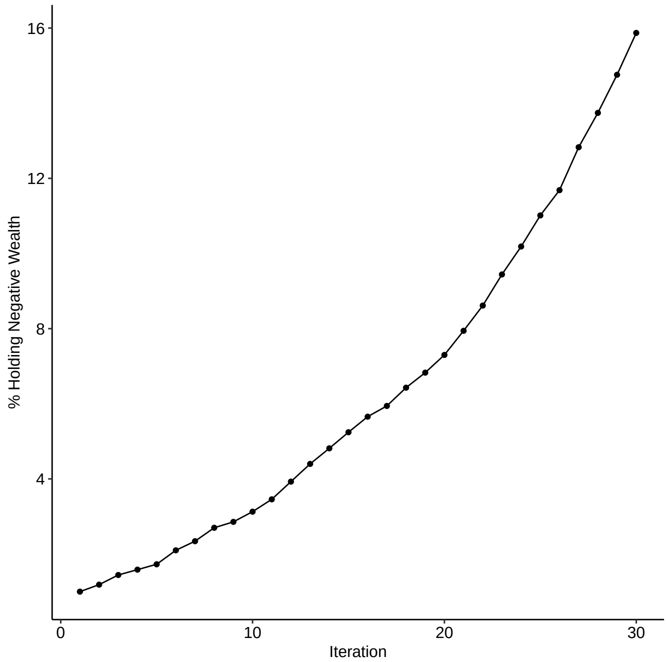


Fig. 2.17 Percent holding negative wealth by iteration through borrowing constraints

KS β-Dist model iterated through negative borrowing constraints. Each iteration is the solution to the model which, starting at zero, lowers the borrowing constraint by 0.1.

2.9 Conclusion

This chapter has presented the canonical heterogeneous agents model of Krusell and Smith (1999), comparing its predictions to a representative agent model and other related Bewley models. I presented the mechanics of the model under different parameterisations. I then showed that a commonly used mechanism for fitting the empirical wealth distribution implies contradictory results when we look more closely at the dynamics over the cycle. In order to fit the empirical wealth distribution at two points in time, before and during the Great Recession, MPCs and the implied individual policy functions for consumption must shift. However, the internal dynamics of the model imply an increase in the MPC for only the poorest agents, consistent with a greater mass of agents near the borrowing constraint. This implies that either preferences changed over the great recession, or something else changed that is not currently captured within the model. I also showed that fitting the fraction of consumers with zero or negative wealth in the KS model with heterogeneous βs implies that the budget constraint must be looser in a recession compared with non-recessionary times, contrary to standard models of financial frictions and empirical evidence on credit availability over the business cycle. In the next chapter, I will look at the possible explanations for what changed over the Great Recession in order to reconcile the dynamics of the model with the cross sectional wealth distributions over the cycle.

Chapter 3

3.1 Introduction

The Great Recession had a large-reaching influences on consumption, saving and the wealth distribution in the US. Bricker et al. (2012) find that over the period 2007 - 2010, median net worth fell 38.8 percent in real terms, and the Survey of Consumer Finances also documents that net worth decreased considerably relative to income; the median net worth-to-income ratio declined from 8.5 in 2007 to 5.6 in 2010. De Nardi et al. (2011) detail that it took almost 12 quarters for total real personal consumption expenditures to return to the previous peak in 2007 Q4. Seen through the lens of the incomplete market heterogeneous agent model discussed in chapter 2, this empirical evidence suggests that the fraction of wealth-poor, high-marginal propensity to consume (MPC) households rose substantially during this time. Other things equal, we should expect there to have been an increase in the aggregate MPC. Such a finding would be in line with the recent estimates of Heathcote and Perri (2018), who find that consumers with low wealth cut their expenditures more sharply than those with high wealth levels during the Great Recession. However, it is also possible that the function itself shifted over the period, given that many of its determinants were also affected by the recession.

Concretely, from previous literature the determinants that could plausibly generate an increase in aggregate MPC over the recession are: 1) the interaction between the model's concave consumption function and a fall in wealth across the distribution 2) an increase in the variance of income shocks, 3) borrowing constraints becoming tighter during recessions. For point 1), as was discussed in chapter 2 in the standard incomplete market model of heterogeneous agents, wealth stocks act as a buffer to smooth consumption against income shocks. This is because there are no Arrow securities; holding capital stocks is the only form of insurance available. Households very close to the borrowing constraint have a precautionary motive to save more, and consume less, in order to avoid hitting the borrowing constraint and potentially violating their Euler equation. A general fall in wealth stocks implies more households in the high-MPC area of the consumption function and therefore an increase in aggregate MPC.

Point 2) is described extensively in Carroll et al. (2014) in a calibrated incomplete markets heterogeneous agents model. They consider two types of income shocks: permanent (highly persistent shocks) and transitory ones. Decomposing income into these two components is a standard way of thinking about income shocks in the literature, and goes back to Friedman (1957). Carroll et al. (2014) show that increases in the variance of permanent shocks do not have a significant effect on the consumption function - this stands to reason, since recessions are temporary, there is little correlation between permanent shocks and aggregate uncertainty. However, an increase in the variance in transitory shock affects the consumption function significantly, by shifting it upwards and also manifesting as a larger aggregate MPC. There is certainly a large literature on the deleterious effects of recessions on labour markets, see for example Elsby et al. (2010) on the Great Recession. Moreover, Guvenen et al. (2014) find that the left-skewness of income shocks is countercyclical.

For point 3), there is ample evidence that borrowing constraints are tighter during periods of falling economic activity. Particularly in financial crises, the sharp drop in lending can worsen and prolong economic downturns (Bernanke and Gertler (1989); Kiyotaki and Moore (1997)). Ludvigson (1999) finds that predictable growth in consumer credit is significantly related to consumption growth in the macroeconomic time series. Gross (1994) estimate using bankruptcy data that MPC out of liquid funds is 20-30% higher during the Great Recession. However, as I detail in chapter 2, in order to fit the proportion of households with negative wealth, the standard incomplete markets model actually implies a *decrease* (ie loosening) of the borrowing constraint over the Great Recession. While this mechanism certainly deserves to be explored, because the current study is concerned with reconciling the incomplete market heterogeneous agent model with empirical evidence, I leave it to future research.

The focus of this chapter is to distinguish between points 1) and 2). I do this by estimating the marginal propensity to consume out of transitory income over the cross-section of income and the business cycle while controlling for point 3), borrowing constraint changes. If the variance in transitory income (point 2) is the mechanism through which aggregate MPC increases, we should expect to see a shift in the consumption function and a steepening towards the origin. Meanwhile if point 1), a fall in wealth interacting with concave consumption function, is occurring we should not find a shift in the consumption function over the whole distribution in a recession. Usually studies estimate the marginal propensity to consume for the whole distribution, and do not allow the possibility for it to vary with economic conditions. My first contribution is to estimate the consumption response response to transitory income shock by income quintile over the business cycle. Secondly, by comparing estimates of the pre-recession and recession consumption function I am able to determine whether the increase in aggregate MPC is more likely due to a shift in the consumption function or a greater mass of individuals in the high-MPC area.

The paper is organised as follows: section 3.2 reviews the related literature, 3.4 describes the data. Section 3.5 describes the empirical estimation strategy and 3.6. Section 3.7 concludes with some suggested avenues for future research.

3.2 Related Literature

There are two major difficulties with getting empirical estimates of the consumption and savings responses to income shocks across the population. The first is data availability: ideally the researcher would have good panel data on income and consumption expenditures. Having a large sample across a number of time period is key to well-estimated results due to the widely-documented measurement error inherent in consumption data. Unfortunately, in the US, this data does not exist within a single dataset over a long time horizon. There are a number of panel data sets, but none contain comprehensive data on both variables over time. The Panel Survey of Income Dynamics (PSID) has extremely accurate data on income (Lusardi (1996)) but the questions it asks on consumption are limited to food and housing expenditure before 1999, and only include good consumption data biennially since 2005. In contrast, the Consumer Expenditure Survey (CEX) from the Bureau of Labor Statistics has excellent data on consumption, whereas income data is limited. Previous authors have circumvented this problem either by using the limited data in one of the two datasets (e.g., Hall and Mishkin (1982)), or by creating a synthetic panel (Attanasio and Davis (1996)). More recently, Blundell et al. (2008) used food demand estimates to impute a measure of non-durable consumption for the PSID from CEX data. I am able to estimate consumption responses to income shocks by utilising a method which requires only 3 consecutive time periods on recently available PSID data.

The second difficulty is in identifying individual income shocks; specifically, difficulty lies in determining the transitory and permanent components. In survey data we only observe total income, so previous approaches have included just working with the change in this variable, for example Krueger and Perri (2005). Other studies have used proxies for transitory income changes, such as unemployment or illness. Another large strand of the literature estimates the consumption response of households to tax rebates (e.g. Kaplan and Violante (2014), Souleles (2002), Johnson et al. (2004)). In both cases, it is unclear the extent to which such events are truly unanticipated. Furthermore, in the latter approach it is unclear what the interaction of expected government spending changes might be. The current paper employs a two stage estimation technique in order to extract the response to transitory income shocks. First, I regress the log of consumption, and the log of income on explanatory variables which capture the predictable parts of consumption and income due to individual heterogeneity, leaving only transitory and permanent shocks in the error term. I then use covariance restrictions to identify a consistent estimator of the covariance between transitory shocks in consumption and income. This method is developed in Blundell et al. (2008), and described in full detail in section 3.5 below.

There are a large number of studies which estimate the MPC over the whole population. Different approaches on distinct datasets, timespans, economic conditions, and on different components of consumption estimate aggregate annual MPC in a large band of between 0.-0.8. For example, Blundell et al. (2008) estimate non-durable MPC to be 0.05, Parker et al. (2013) estimate it in the region of 0.5-0.9 for total personal consumtpion expenditures, Souleles (2002) estimate non-durable MPC in the range 0.6-0.9; Jappelli and Pistaferri (2010) and Carroll et al. (2017) provide an excellent survey. Research that looks at heterogeneity of MPC across the population includes Jappelli and Pistaferri (2014) who use Italian Survey data which specifically asks respondents how much they would consume out of a transitory income shock. They find on average across the population a value of 0.48, with low cash-on-hand individuals exhibiting a much higher value than high cash-on-hand types. Another study which looks at MPC over portions of the distribution is Kaplan et al. (2014), whose paper also uses the method outlined in Blundell et al. (2008) to estimate marginal propensities for subsets termed ‘wealthy hand-to-mouth’ (W-HtM), ‘poor hand-to-mouth’ (P-HtM) and ‘not hand-to-mouth’ (N-HtM) . Those labelled ‘hand-to-mouth’ are distinguished as those holding very little wealth in liquid asset classes, and are 'Wealthy' if they also hold sizeable amounts of illiquid assets, and 'Poor' if they do not. They find that both HtM types have dramatically higher MPCs (0.44) than N-HtM (0.10) types. I utilise their two measures of poor and wealthy hand-to-mouth individuals to control for changing borrowing constraints over the Great Recession, described in section 3.4.3, below.

The contribution of this chapter is looking at MPC over the business cycle, for which the literature is sparse. Gross et al. (2016) is - to my knowledge - unique in estimating the variation of MPC over the business cycle. Using bankruptcy data they estimate MPC out of liquid funds to be around 0.37 in good times, and 20-30% higher during the Great Recession, suggesting a large role for tightened liquidity constraints during bad economic times in driving this variation. However, their study is based on US consumers that have previously filed for bankruptcy which limits the extent to which the results can be generalised to the population as a whole. It also differs from the current study in that the shock to income (the lifting of bankruptcy flags) is predictable, whereas I assume that future shocks are fully unanticipated. Finally, this paper uses survey-weighted data to provide estimates applicable for the full population.

3.3 The Average Propensity to Consume and Save

The left hand side of figure 3.18 shows an estimate of the average propensity to consume, calculated from the PSID by dividing average consumption by the average level of income for the pre-recession period (2002-2006) and recession period (2008-2012) by the average level of income over the same time horizons. In this estimation, the identity of households is fixed by quintile at the beginning of the period, ie. the 2002 - 2006 average consumption for the bottom quintile is for households in the bottom quintile in 2002 (regardless of quintile in the following years). This estimate suggests that low-income households consume a much greater fraction of their income compared to their high-income counterparts on average. It also provides suggestive evidence that the consumption function may not have not change markedly over the recession except for a slight steepening at the bottom quintile. However, it is important to note that this is an estimate of the average, rather than the marginal propensity to consume, and it does not does not control for household characteristics, borrowing constraints, or distinguish between the components of income or consumption shocks.

The right hand side of 3.18 shows the change in total net wealth calculated from PSID data by dividing the change in net wealth over the time periods by average income, plotted for the income quintiles. Clearly, there is a stark difference in pre-recession and recession periods. In the pre-recession period the change in total wealth is much greater for higher income individuals, and the difference in the pre-recession and recession periods is stark. During 2002-2006, total net wealth change was much greater than in the 08-12 period across the distribution. Falls in wealth were experienced by the poorest quintile in the recession period, and the rest of the distribution saw very small increases. Occasionally the change in wealth is taken to be an estimate of the average savings rate[24], which would suggest a difficulty in reconciling the left and right graphs since MPC=1-MPS and we see a shift in 'saving' but not consumption. However, it is important to note that the change in net wealth also contains capital gains and losses. The difference in the two series could be entirely explained by passive wealth accumulation or deaccumulation.

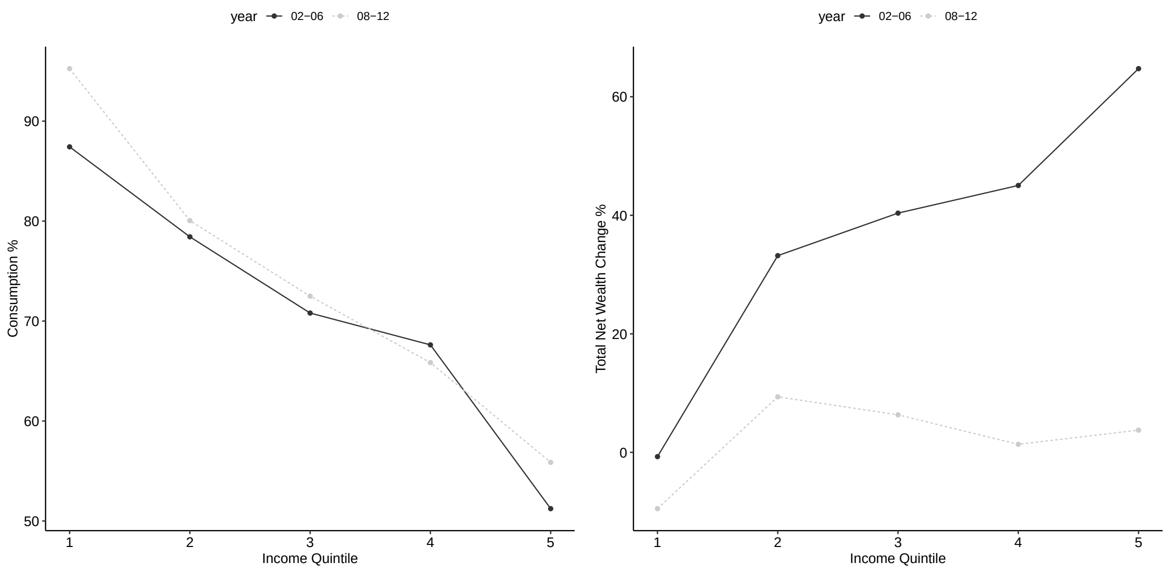


Fig. 3.18 Empirical Distributions of Average Consumption and Average Wealth Change by Year and Income Quintile

Average consumption rates divided by average income by income quintile (left); average net total wealth change divided by average income by income quintile, (right). Pre-recession period: 2002-2006, recession: 2008-2012. Calculated by the author from survey-weighted PSID data.

[24]See, for example, Dynan et al. (2004).

3.4 Data

In the first stage regressions, detailed in section 3.5, I estimate the predictable elements of consumption and income changes in order to leave only permanent and transitory shocks in the residual for the second stage regressions which recover the MPC. For this first stage, I use data from the Panel Study of Income Dynamics public use dataset, a nationally representative longitudinal survey of US households which is completed biennially. I combine it with PSID wealth supplements which provides detailed data on wealth and assets. For the pre- and recession periods (2002-2006 and 2008-2012) I joined each adjacent year by finding those households that had the same household head. In other words, in order to increase the sample size, I only require the households to be the same within the periods, but they can differ across the periods. The appendix repeats the analysis with a smaller, balanced panel over 2002-2012 and finds very similar results. The additional criteria for inclusion in the sample include having a household head between the 22-65 and non-blank data not only for consumption and income, but also all demographic and other control variables. In this section, I detail the properties of the dependent and independent variables for the first state regression.

It is important to note that the PSID is known to undersample the most wealthy 1-2% (Pfeffer et al. (2016)), so I use the weights and strata information provided. The design of the PSID is a complex survey, therefore working with unweighted PSID data would violate the assumption that observations are i.i.d., since the complex survey design creates data with correlations between observations and unequal sampling probabilities. It is also a top-coded survey for purposes of anonymity, I drop these observations since the true values are unknown. This is innocuous since the very top of the income and wealth distributions have so little mass, they do not matter for aggregate MPC.

3.4.1 Consumption data in the PSID

Since its release, consumption data in the PSID is starting to become much more widely used in research, notably Blundell et al. (2016). However its introduction has been gradual, with extra expenditure categories added over time. Figure 3.19 shows the amounts calculated including food, transport, childcare, healthcare, education and housing (consumption). In the 2004 survey, vacations, recreations and clothing were added to the survey (consumption plus). There is some difference in the consumption amounts including and excluding the extra categories, both in levels and in co-movement with the cycle. Unfortunately, because the method of estimating marginal propensities requires a minimum of three time periods (see section 3.5 below), I use consumption rather than consumption plus in the estimations. I drop observations with negative or zero consumption values, around 0.01% of the sample per year.[25]

Table 3.4 compares the mean values of consumption and consumption plus to the corresponding values reported from the Consumer Expenditure Survey (CEX). Clearly, the PSID means are smaller relative to the CEX means, even when including the additional expenditure categories. It is likely that, even with extra consumption categories, because the PSID coverage is not as extensive as the CEX, it is underestimating consumption. It is also possible that the mean values are lower because the PSID is know to undersample the richest households. However, the dynamics of consumption over the Great Recession are very similar in both the CEX and the PSID.

Table 3.4 Mean Consumption Comparison

Year	$\bar{c}_{i,t}^{CEX}$	$\bar{c}_{i,t}$	$\bar{c}_{i,t}^{\text{PLUS}}$
2002	40677	28573	NA
2004	43395	35612	39559
2006	48400	38870	43112
2008	50486	37816	41837
2010	48109	37890	41502
2012	51442	38213	41878

$\bar{c}^{CEX}$ is mean consumption available from the CEX
$\bar{c}_t$ is the corresponding estimate in the PSID data
$\bar{c}_t^{\text{PLUS}}$ is mean PSID consumption plus extra expenditure categories, author's calculations.

[25]Negative consumption values come from imputed consumption values from the PSID, which uses a linear regression to predict missing consumption values.

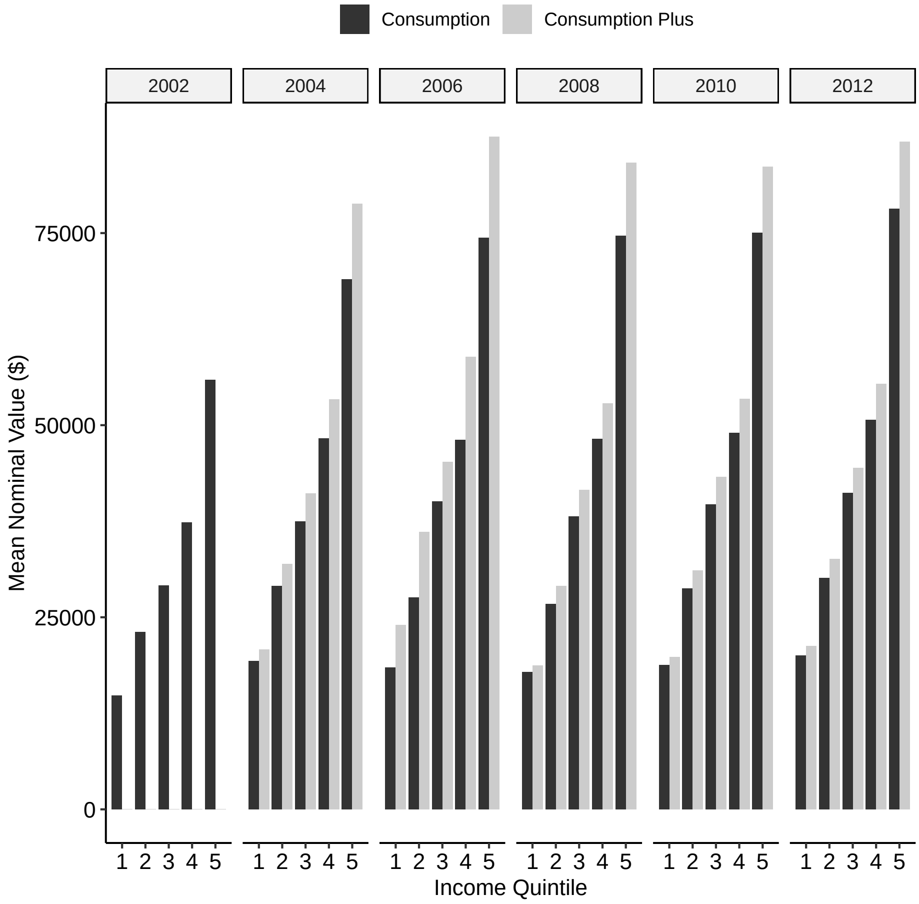


Fig. 3.19 Mean Consumption in the PSID

Consumption = food + transport + childcare + healthcare + education + housing; Consumption Plus = consumption + vacations + recreation + clothing

3.4.2 Measuring After-Tax Income

The PSID reports total taxable income of the household in the preceding year to the survey, ie., $y_{it} + T_t$ where T is a lump sum tax. However, for the purposes of understanding consumption and saving responses to income changes, I calculate after-tax income. It is important to use after-tax income because changes in taxation could change consumption responses. To do this, I use the TAXSIM program from NBER, which estimates the tax lump-sum given details of income, family composition and deductions. I use the method outlined in Butrica and Burkhauser (1997) by adapting code from Kimberlin et al. (2014) to include 2013 data. Clearly, it is very important that after-tax income is well measured, so table 3.5 compares average (mean) after-tax income estimated from the CEX versus the corresponding quantity estimated from the PSID using TAXSIM.

Table 3.5 After-tax Income Comparison

Year	$\bar{y}_t^{CEX}$	$\bar{y}_t^{alt}$
2002	46934	53858
2004	52287	61565
2006	58101	65033
2008	61774	62466
2010	60712	62766
2012	63370	67629

$\bar{y}^{CEX}$ is mean after-tax income available from the CEX
$\bar{y}_t$ is the corresponding estimate in the PSID data using TAXSIM from the NBER, author's calculations

The PSID values, although larger, are closer to CEX estimates in this case, likely because the PSID covers more income categories, though it could also be due to an underestimate of taxes in the TAXSIM programme. However, the dynamics over the sample are again similar in both surveys.

3.4.3 Explanatory variables for Predictable Consumption/Income

Demographic and Economic variables

Demographic controls are all taken to be the values of the household head (which in the PSID are overwhelmingly male). Controls include a dummy for year of birth, dummies for education which takes three levels: up to high school education (low), college educated (medium), or some postgraduate (high). I control for employment status which can take values employed, unemployed, retired or inactive. Also included are race dummies (taking values white, black, and other), and variables for family size and number of kids in the family unit. I include dummies for whether the family has extra income coming from those outside the household, extra dependents outside the family unit and categorical dummies for region: North East, Midwest, South, West. Finally, I include controls for total net wealth level in thousands of dollars.

Controls for the borrowing constraint

Following Kaplan and Violante (2014) I distinguish two types of household: poor hand-to-mouth (P-HtM) and wealthy hand-to-mouth (W-HtM) which, due to a lack of liquid assets on hand, can come up against binding borrowing constraints. Poor hand-to-mouth households are defined as being at the credit limit when their illiquid wealth holdings and liquid wealth holdings are not positive, and their cash-on-hand and available credit is less than half their yearly income; i.e.:

$$a_{it} \leq 0, \quad m_{it} \leq 0 \quad \text{and} \quad m_{it} \leq y_{it}/2 - \underline{m}_{it}$$

where a_{it} is holdings of illiquid wealth by household i in period t, m_{it} is average balances of liquid wealth over period t, y_{it} is total household income and $\underline{m}_{it}$ is the household's credit limit.

Wealthy hand-to-mouth households are defined similarly, with the key difference being that they own positive illiquid assets, i.e.:

$$a_{it} \geq 0, \quad m_{it} \leq 0 \quad \text{and} \quad m_{it} \leq y_{it}/2 - \underline{m}_{it}$$

In the PSID, illiquid wealth is calculated as the sum of home equity, other real estate equity, private annuities and other assets. Liquid wealth is the sum of checking and saving accounts, money market funds, certificates of deposits, savings bonds, treasury bills, stocks net of liquid debt which includes all debt other than mortgage debt. Figures 3.20 and 3.21 show the fraction of Poor HtM and Wealthy HtM households in the PSID, the fractions are consistent with those reported by Kaplan and Violante (2014). The fraction of wealthy hand-to-mouth households falls over the Great Recession while the fraction of poor rises. Interestingly, calculated for the quintiles of income, the fraction of P-HtM exhibits a strong negative relationship, while the fraction of W-HtM is an inverted U-shape in each year. The fractions within a given quintile for the wealthy hand-to-mouth are relatively stable over the Great Recession, while the fraction of P-HtM in the poorest income quintiles rises markedly. This is suggestive evidence that borrowing constraints became more likely to bind for the very poorest hand-to-mouth households during the recession, with less of a noticeable effect for the wealthy hand-to-mouth. To control for binding borrowing constraints in the consumption and income regressions, I use a dummy variable for Poor and Wealthy HtM households, equal to 1 when a household falls into the respective categories and 0 otherwise.

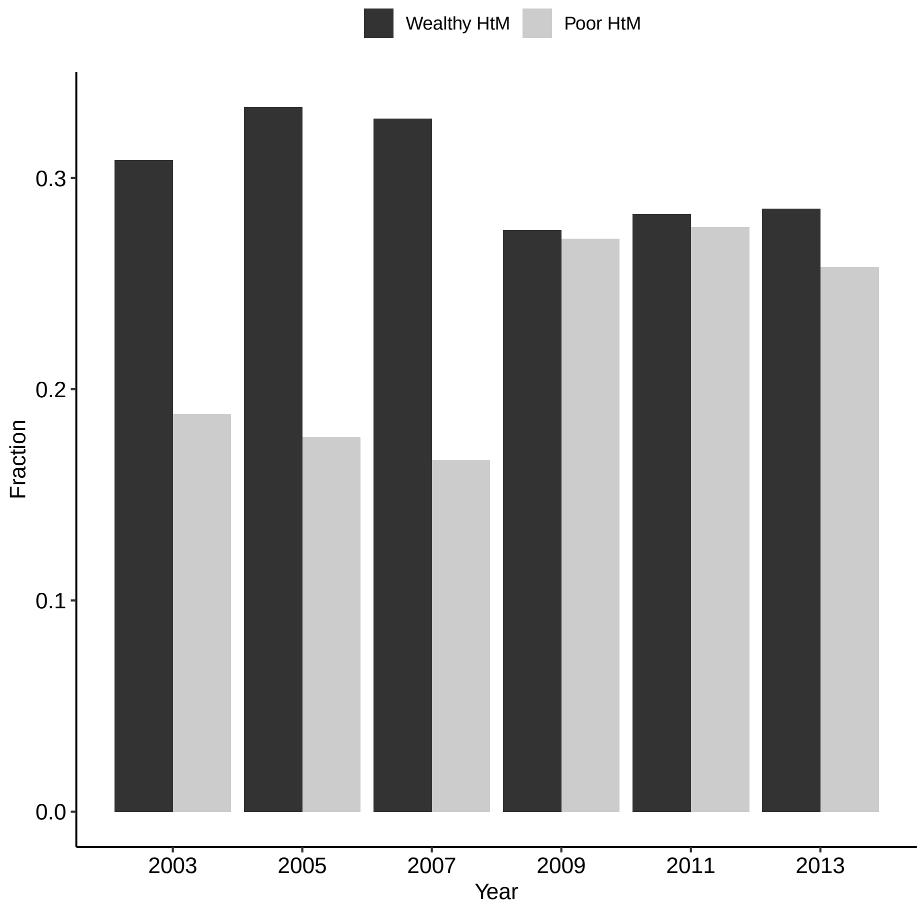


Fig. 3.20 Hand-to-mouth households in the PSID

Fraction of Poor hand-to-mouth (P-HtM) and Wealthy hand-to-mouth (W-HtM) consumers in the PSID by year, author's calculations

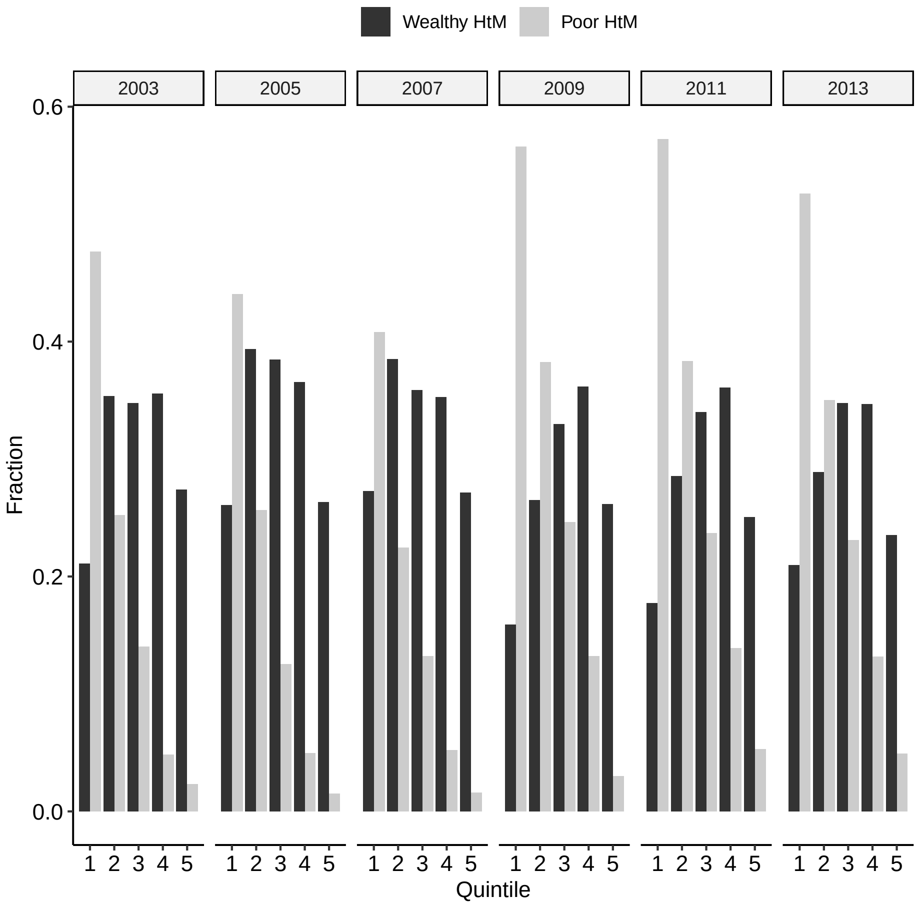


Fig. 3.21 Hand-to-mouth households by income quintile in the PSID

Fraction of Poor hand-to-mouth (P-HtM) and Wealthy hand-to-mouth (W-HtM) consumers in the PSID by year and quintile, author's calculations.

3.5 Econometric Model & Identifying Assumptions

3.5.1 Estimating the Marginal Propensity to Consume and Save

Following Blundell et al. (2008) and Kaplan et al. (2014), assume income follows the process:

$$\log Y_{i,t} = \mathbf{Z}'_{it}\mathbf{\Phi}_t + P_{i,t} + \epsilon_{i,t} \tag{3.12}$$

where i is an individual at time t, Y is income, $\mathbf{Z}$ is a set of observable income characteristics, $P_{i,t} = P_{i,t-1} + \xi_{i,t}$ is a martingale permanent income process with i.i.d. shock ξ; and ϵ is an i.i.d. transitory income shock. Blundell et al. (2008) show that such a specification provides a good approximation to the solution of a life cycle optimization problem where agents have CRRA utility.

By estimating equation 3.12 and recovering the first-differenced residuals, I obtain unexplained income growth:

$$\Delta\widehat{y_{i,t}} = \xi_{i,t} + \Delta\epsilon_{i,t}$$

where $\widehat{y_{i,t}} = \log Y_{i,t} - \mathbf{Z}'_{it}\hat{\mathbf{\Phi}}_t$.

Consumption is assumed to be subject to the same processes but with loading factors (marginal propensities) on permanent and transitory income shocks $\psi^P_{i,t}$ and $\psi^T_{i,t}$, giving unexplained growth as:

$$\Delta\widehat{c_{i,t}} = \psi^P_{i,t}\xi_{i,t} + \psi^T_{i,t}\Delta\epsilon_{i,t}$$

where $\Delta\widehat{c_{i,t}}$ is estimated first-differenced consumption residuals $\widehat{c_{i,t}} = \log Y_{i,t} - \mathbf{Z}'_{it}\hat{\mathbf{\Psi}}_t$.

The covariance restriction necessary for identification of the marginal propensity to save from transitory income shocks are that individuals have no foresight about future shocks, i.e. $\text{cov}(\Delta c_{i,t}, \epsilon_{i,t+1}) = \text{cov}(\Delta c_{i,t}, \xi_{i,t+1}) = 0$.

The true marginal propensity to consume out of a transitory shock is given by:

$$\text{MPC}_t = \frac{\text{cov}(\Delta c_{i,t}, \epsilon_{i,t})}{\text{var}(\epsilon_{i,t})}$$

Which, using the covariance restrictions, can be estimated consistently via an instrumental variable regression of $\Delta\widehat{c_{it}}$ on $\Delta\widehat{y_{i,t}}$ instrumented by $\Delta\widehat{y_{i,t+1}}$:

$$\widehat{\text{MPC}_t} = \frac{\text{cov}(\Delta\widehat{c_{i,t}}, \Delta\widehat{y_{i,t+1}})}{\text{cov}(\ \Delta\widehat{y_{i,t}}, \Delta\widehat{y_{i,t+1}})} \tag{3.13}$$

By using this methodology on a panel simulated from an incomplete insurance model in which they can compare estimated and true values, Kaplan and Violante (2010) show that this method works extremely well for estimating transitory shocks and is not biased in the presence of binding borrowing constraints. The estimation requires 3 periods of data for consumption: $t-1, t, t+1$ so I drop households with fewer than 3 consecutive years of observations in each of the two time periods. To get an estimate of the marginal propensity to consume across the distribution, I estimate equation 3.13 for the income quintiles at the beginning of the pre-recession and recession sample period (2002 and 2008).

3.6 Results

In this section I begin with a summary of the first-stage regression output, the result of estimating the income process in equation 3.12 and the corresponding consumption equation. I then discuss the second-stage regression results which use the residuals from the first-stage estimation to estimate the marginal propensity to consume. I first discuss the results over the entire distribution for the pre-recession and recession periods and then show the estimates over the income quintiles.

Table 3.6 details the results of the first-stage regressions to extract the predictable parts of consumption and income. Though a means to estimating the marginal propensity to consume, these results merit inspection in their own right. Year dummies show time growth in consumption and income which is greater prior to the Great Recession. As we might expect, income levels are greater by approximately 6 and 17 percent for the medium and high educated, respectively, relative to the low educated. This greater income level does not transfer fully into consumption, which are greater by approximately 3 and 10 percent for the same groups. Being a race other than white is associated with lower income and consumption levels, while family size increases both. More kids in the household is associated with lower consumption and income levels, as is being unemployed, retired or inactive. Comparing the pre-recession and recession periods by employment status, the penalty to consumption and income increases for all non-employment in the recession period. Being in a region that is not the North East is associated with a consumption and income penalty of between 2 and 5 percent, but this does not seem to change dramatically with the business cycle. Both Poor Hand-To-Mouth households (those with cash on hand and available credit at less than half their yearly income and a negative illiquid net worth position), and Wealthy Hand-To-Mouth households (those with cash on hand and available credit at less than half their yearly income but a positive illiquid net worth position) see a penalty to consumption and income. Those that are P-HtM have lower consumption levels of approximately 8 percent relative to non-HtM households, and lower income levels of 12 percent. Meanwhile the associated reduction for W-HtM households is not significant from zero for consumption, but associated with 5 percent lower income levels. This is suggestive evidence that borrowing constraints are more likely to be binding for P-HtM, since it is associated with lower consumption. We also see that the coefficient on the poor hand-to-mouth dummy decreases income by a lesser amount in the recession period, by 6 percent compared with 8 percent. The coefficient on the poor hand-to-mouth dummy decreases consumption by a lesser amount in the recession period, 13 to 12 percent. Overall, it suggests that the consumption to income ratio in the poor hand-to-mouth sample increased over the recession period, suggesting the average propensity to consume rose in this group.

Table 3.6 First Stage Regressions

	$\log(\widehat{c_{it}})$		$\log(\widehat{y_{it}})$	
	2003-2007	2009-2013	2003-2007	2009-2013
	(1)	(2)	(3)	(4)
Year=2004	0.053***		0.029***	
	(0.002)		(0.003)	
Year=2006	0.077***		0.051***	
	(0.004)		(0.003)	
Year=2010		0.007**		0.006
		(0.002)		(0.003)
Year=2012		0.017***		0.025***
		(0.002)		(0.004)
Education=Medium	0.034***	0.038***	0.063***	0.063***
	(0.006)	(0.006)	(0.008)	(0.009)
Education=High	0.105***	0.109***	0.167***	0.175***
	(0.006)	(0.007)	(0.010)	(0.010)
Race=Black	−0.045***	−0.037***	−0.069***	−0.068***
	(0.007)	(0.007)	(0.008)	(0.007)
Race=Other	−0.009	−0.004	−0.047**	−0.053**
	(0.014)	(0.009)	(0.014)	(0.015)
Family Size	0.069***	0.084***	0.091***	0.108***
	(0.004)	(0.004)	(0.005)	(0.005)
Number of Kids	−0.047***	−0.058***	−0.071***	−0.081***
	(0.004)	(0.004)	(0.005)	(0.006)
Status=Unemployed	−0.028*	−0.058***	−0.082**	−0.107***
	(0.011)	(0.009)	(0.019)	(0.017)
Status=Retired	−0.055***	−0.075***	−0.089***	−0.106***
	(0.006)	(0.005)	(0.010)	(0.008)
Status=Inactive	−0.061***	−0.097***	−0.121***	−0.152***
	(0.007)	(0.007)	(0.010)	(0.011)
Extra Family Income	0.012*	0.003	0.027**	0.027**
	(0.005)	(0.007)	(0.007)	(0.008)
Region=Midwest	−0.043***	−0.053***	−0.036**	−0.053**
	(0.008)	(0.010)	(0.011)	(0.012)
Region=South	−0.027**	−0.033**	−0.032*	−0.038**
	(0.009)	(0.010)	(0.013)	(0.012)
Region=West	−0.022*	−0.042***	−0.037**	−0.050***
	(0.008)	(0.009)	(0.009)	(0.010)
Kids outside Family Unit	0.025**	0.023***	0.059***	0.062***
	(0.006)	(0.005)	(0.012)	(0.008)
Poor-HtM	−0.078***	−0.061***	−0.128***	−0.122***
	(0.006)	(0.006)	(0.008)	(0.009)
Rich-HtM	−0.005	−0.012	−0.053***	−0.056***
	(0.005)	(0.006)	(0.007)	(0.008)
Total Wealth ($1000s)	0.0002**	0.0004*	0.001**	0.001**
	(0.0001)	(0.0001)	(0.0001)	(0.0002)
Constant	11.383***	11.668***	11.731***	11.693***
	(0.015)	(0.022)	(0.022)	(0.052)
Year of Birth	Yes	Yes	Yes	Yes
N	13,281	14,820	13,281	14,820

Notes:

***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Survey-weighted generalised least squares regression for the years 2002, 2004, 2006 (columns 1 and 3) and 2008, 2009, 2011 (columns 2 and 4) in the PSID

Table 3.7 details the results of the instrumental variable regression estimating the marginal propensities to consume across the whole distribution over the pre-recession and recession periods - giving an estimate of the aggregate MPC. The findings for the marginal propensity to consume are in line with other empirical evidence, suggesting that the MPC out of transitory income is non-zero, a result which is significant at 1%. The results suggest that on average, households consumed 10% of a transitory income shock over the pre-recession period 2002-06, and this increased to 16% in the recession period, 2008-12. The difference in the estimated MPCs is also significant at 1% over the pre-recession and recession periods. I also include as a robustness check an estimate of the implied marginal propensity to save, where saving is defined as income minus consumption, so we should find MPC $\approx$ 1-MPS. The marginal propensity to save implied by $y_{i,t} - c_{i,t}$ is not exactly equal to $1 - \Delta c_{i,t}$ due to measurement error, but the rough approximation holds, as does the trend over the recession.

Table 3.7 Whole distribution estimates of MPC & MPS

	MPC	
	03-07	09-13
	0.1^{***}	0.162^{***}
	(0.027)	(0.029)
N	4535	5160

Turning to the estimates over the income distribution, tables 3.8 and 3.9 reports the regression output over the pre-recession and recession periods which figure 3.22 shows graphically. On the left of figure 3.22, the MPC is downward sloping, implying an upward-sloping consumption function. The very poorest quintile consumes around

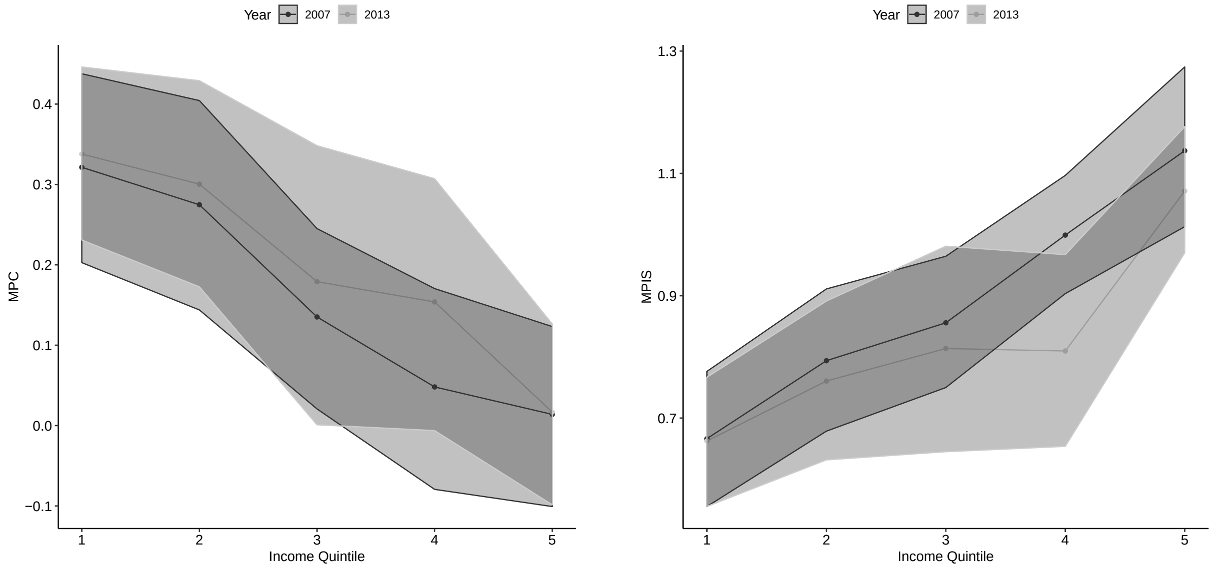


Fig. 3.22 Empirical Distribution of MPC and implied MPS by year and quintile

Estimated marginal propensity to consume (left) and marginal propensity to save (right) by income quintile and time: pre-recession period (2002-2006) , recession (2008-2012)

35% of a transitory income shock, this reduces down to a value that is not significantly different to 0% for the highest income quintiles. Note that we see downward sloping relationship between MPC and income despite controlling for borrowing constrained households, a factor which is known to generate such a relationship. This is suggests that there is an certainly an important role for another mechanism to create heterogeneity in the MPC over the distribution of income. One such mechanism that was discussed in chapter 2 - heterogeneous preferences in the form of discounting - is certainly not ruled out as a candidate by these results - assuming that heterogeneity in discounting is not perfectly captured by observable characteristics.

Lastly, and most significantly for this study, we see that the MPC over the quintiles did not exhibit a significant upward shift or a steepening near the origin over the pre-recession to recession period. We also see the same result on the balanced panel (see appendix C.1), so differences in preferences across the two samples is not driving the result. This result is more consistent with the narrative of a movement along the consumption function generating higher aggregate MPCs. Such a movement, I have argued, is more consistent with an interaction of a downward-sloping consumption function and an increase in mass at the higher-MPC end rather than a shift in the consumption function.

Table 3.8 IV regression: $\Delta c_{i,t}$ 2002-2006 for Income Quintiles

	$\Delta\widehat{c_{i,t}}$				
	(1)	(2)	(3)	(4)	(5)
$\Delta\widehat{y_{i,t}}$	0.321^{***}	0.275^{***}	0.135^{**}	0.048	0.014
	(0.059)	(0.065)	(0.057)	(0.063)	(0.056)
N	879	882	878	881	856
R^2	0.258	0.154	0.073	0.019	0.006
Residual Std. Error	0.078 (df = 877)	0.091 (df = 880)	0.103 (df = 876)	0.116 (df = 879)	0.140 (df = 854)

Notes: ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Instrumental variable regression of $\Delta\widehat{c_t}$ on $\Delta\widehat{y_t}$ instrumented by $\Delta\widehat{y_{t+1}}$ for the income quintiles, 2002-2006

Table 3.9 IV regression: $\Delta c_{i,t}$ 2008-2012 for Income Quintiles

	$\Delta\widehat{c_{i,t}}$				
	(1)	(2)	(3)	(4)	(5)
$\Delta\widehat{y_{i,t}}$	0.338***	0.300***	0.179**	0.154*	0.017
	(0.054)	(0.065)	(0.087)	(0.079)	(0.057)
N	984	984	981	978	960
R^2	0.175	0.127	0.091	0.072	0.008
Residual Std. Error	0.088 (df = 982)	0.098 (df = 982)	0.114 (df = 979)	0.118 (df = 976)	0.136 (df = 958)

Notes:

***Significant at the 1 percent level.

**Significant at the 5 percent level.

*Significant at the 10 percent level.

Instrumental variable regression of $\Delta\widehat{c_t}$ on $\Delta\widehat{y_t}$ instrumented by $\Delta\widehat{y_{t+1}}$ for the income quintiles, 2008-2012

3.7 Conclusion

In this chapter, I argued that over the Great Recession, rising aggregate marginal propensities to consume could best be explained by two mechanisms according to the standard incomplete markets model of heterogeneous agents. Either the cause was an interaction between falls in wealth and a concave, but static, consumption function; or an increased variance in transitory shocks leading to a shifted consumption function. I estimated the marginal propensity to consume out of transitory income over the pre-recession and recession periods and over the quintiles of the distribution. I provided evidence that the MPC varies greatly over the distribution of income, with income-poor housholds consuming around 35% of a transitory income shock and income-rich housholds consuming none. These results certainly accord with the large range of estimates of MPC found in different datasets and components of consumption and provides a motivation for heterogeneity in discount factors. The estimates also showed that the consumption function did not change significantly over the pre-recession and recession periods, suggesting that the first explanation, the interaction between a concave consumption function and a fall in wealth across the distribution, is more plausible. Of course, due to the presence of significant sampling variation inherent in surveys we don't have the power to distinguish between a very small shift in the consumption function and no change at all. However, what is certain is that the magnitude of the shift in the consumption implied by a standard incomplete markets heterogeneous agent model that is calibrated to the wealth distribution in the pre-recession and recession periods, shown in chapter 2, is far too high to be consistent with the evidence presented in this chapter. This leaves an open question for future research, in terms of reconciling the empirical dynamics of the wealth distribution over the cycle with models of heterogeneous agents.

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A. Chapter 1 Supplementary Material

A.1 Marginal Effects and Decomposition of the Tobit Model

A.1.1 Marginal Effects

The Tobit model can be expressed as:

$$y_i = \begin{cases} X_i\beta + u_i, & \text{if} \quad X_i\beta + u_i > 0 \\ 0, & \text{otherwise} \end{cases}$$

where $i = 1, 2, ..., N$ with N the number of observations, y_i is the dependent variable. X is a vector of independent variables, β is a vector of coefficients and $u \sim N(0, \sigma^2)$ is the error term.

Unlike in an OLS regression, the marginal effect in equation 1.4 of the main text has to be separately calculated. While in an OLS regression the marginal effect is simply $\frac{\partial E(y|X)}{\partial X_j} = \beta_j$, in Tobit the marginal effect can be written as follows:

$$\frac{\partial E(y|X)}{\partial X_j} = P(y > 0|X)\beta_j \tag{A.1}$$

To get an estimate of the marginal effect, we assume a standard normal distribution of the data and we maximise the log-likelihood function of the tobit model w.r.t β and σ^2. This will yield maximum likelihood estimates and, assuming that we have specified the model correctly, it will give us consistent and asymptotically efficient estimators for both β and σ^2. We can then use $\hat{\beta}$ and $\hat{\sigma}$ to estimate the function $P(y > 0|X)$. Using the appropriate expression for the standard normal distribution, we obtain $\hat{P}(y > 0|X) = \frac{1}{N}\sum_{i=1}^{N} F(X_i\hat{\boldsymbol{\beta}}/\hat{\sigma})$, where $F(.)$ is the CDF of a standard normal and N are the number of observations. Thus the marginal effect at the average is estimated as:

$$\frac{\partial \widehat{E(y|X)}}{\partial X_j} = \underbrace{\frac{1}{N}\sum_{i=1}^{N} F(X_i\hat{\beta}/\hat{\sigma})}_{\text{APE scale factor}}\, \hat{\beta}_j$$

Thus, for the purpose of interpretation of marginal effects, all coefficients that appear in the regression tables have to be multiplied by the APE scale factor to obtain the estimated marginal effect.

A.1.2 Decomposition of the Tobit Model

Tobin (1958) shows that for the Tobit model the expected value of y is:

$$E(y|X) = X\beta F(z) + \sigma f(z) \tag{A.2}$$

where $z = X\beta/\sigma$, $f(z)$ is the unit normal density and $F(z)$ is the corresponding CDF.

Furthermore, the expected value of y for observations above the limit, $y > 0$, is $X\beta$ plus the expected value of the truncated normal error term (see Amemiya (1973)):

$$\begin{aligned} E(y|X, y > 0) &= E(y|X, u > -X\beta) \\ &= X\beta + \sigma \frac{f(z)}{F(z)} \end{aligned} \tag{A.3}$$

From A.2 and A.3, the relationship between $E(y|X)$ and $E(y|X, y > 0)$ is simply:

$$E(y|X) = F(z)E(y|X, y > 0) \tag{A.4}$$

From A.3, taking the partial derivative with respect to the jth independent variable X_j and noting that $F'(z) = f(z)$ and $f'(z) = -zf(z)$ gives:

$$\frac{\partial E(y|X, y > 0)}{\partial X_j} = (1 - zf(z)/F(z) - f(z)^2/F(z)^2) * \beta_j \tag{A.5}$$

From which $(1 - zf(z)/F(z) - f(z)^2/F(z)^2)$ gives the fraction of the mean total response is due to the response above the limit, equation 1.6.1 in the main text. Taking the partial derivative of A.4 with respect to X_j gives:

$$\frac{\partial E(y|X)}{\partial X_j} = F(z)\frac{\partial E(y|X, y > 0)}{\partial X_j} + E(y|X, y > 0)\frac{\partial F(z)}{\partial X_j} \tag{A.6}$$

which, using the fact that $F(z) = P(y > 0|X)$ and $\partial F(z)/\partial X_j = (\beta_j/\sigma)F(z)$ we can re-write as equation A.1. Plugging A.5 into A.6 gives the marginal effect for the Tobit:

$$\frac{\partial E(y|X)}{\partial X_j} = \frac{1}{N}\sum_{i=1}^{N} F(X\beta/\sigma)\beta_j \tag{A.7}$$

Following McDonald and Moffitt (1980), using the estimates of β and σ we can get estimates for all parts of the decomposition in equation A.6 at the average by recovering the corresponding z:

$$F(z)\hat{\beta}_j = \frac{\partial E(y|X)}{\partial X_j} = \frac{1}{N}\sum_{i=1}^{N} F(X_j\hat{\beta}/\hat{\sigma})\hat{\beta}_j$$
$$z = F^{-1}(X_j\hat{\beta}/\hat{\sigma})$$

B. Chapter 2 Supplementary Material

B.1 The Krusell Smith Algorithm (KSSim)

KSSim finds the coefficients of the parametrised policy rules for individual agents by using time iteration, a projection technique I will describe below. It then separately finds the parameters of the aggregate laws of motion using data simulated by using these individual policy rules. It compares the consistency of the two using an ordinary least squares projection.

B.2 Solving the Individual Problem with Time Iteration

Just as the Bellman equation has an associated operator that maps value functions into value functions, the Euler equation has an Euler operator that maps policy functions into policy functions. Although the Euler equation is not a contraction mapping like the Bellman, it can be shown that an iterative procedure on the Euler equation, known as time iteration, is equivalent to value function iteration; computationally it is a much more efficient technique.

To form the time iteration problem we start with equation 2.8a and substitute out for c' using the budget constraint. Then we can find functions that satisfy the functions $k' = g_{k'}(k, e, z, \bar{K}; \phi)$ and $\lambda = g_\lambda(k, e, z, \bar{K}; \phi)$ according to:

$$
\begin{aligned}
U_{k'}(c) + \lambda = \beta \sum_{z' \in Z} \sum_{e' \in E} &[(1 + r' - \delta) U_{k'}((1 + r' - \delta)k' \\
&+ [(1 - \tau')\bar{l}' e' + \mu(1 - e')]w' - g_{k'}(k', e', z', \bar{K}'; \phi))
\end{aligned}
\tag{B.1}
$$

where $U_{k'}$ is the derivative of U with respect to k', The policy function and Lagrange multiplier must satisfy the complementary slackness conditions, $\lambda \geq 0$, $k' \geq 0$ and $\lambda k' = 0$. However, solving B.1 involves having to solve jointly for the policy function and Lagrange multiplier. To circumvent the need for this, we drop the multiplier. The policy function obtained may violate the constraint $k' > 0$, but the algorithm deals with this by simply forcing the capital choices to take positive values. Using this trick, and assuming logarithmic utility, we can re-express B.1 as:

$$\frac{1}{c} =$$
$$\beta \sum_{z' \in Z} \sum_{e' \in E} \left[\frac{(1 + r' - \delta)}{((1 + r' - \delta)k' + [(1 - \tau')\bar{l}' e' + \mu(1 - e')]w' - g_{k'}(k', e', z', M'; \phi))} \right]$$

This equation provides the basis for the time iteration algorithm. To apply this method in practice, we must prespecify a grid of possible values for k to take and solve the right hand side (RHS) of B.1 for each one of the nodes of the grid. The right hand side takes next period's aggregate capital stock K' as an input through $r' = \alpha z' \left(\frac{K'}{\bar{l}' L(z')} \right)^{\alpha - 1}$ and $w' = (1 - \alpha) z' \left(\frac{K'}{\bar{l}' L(z')} \right)^{\alpha}$. This is retrieved by updating the previous period's distribution by the aggregate transition probabilities for each employment state:

$$K'_{e_b} = \frac{(1 - L(z))\pi_{e'_b, z' | e_b, z} \hat{K}_{e_b} + L(z)\pi_{e'_b, z' | e_b, z} \hat{K}_e}{(1 - L(z'))}$$

$$K'_{e_g} = \frac{(1 - L(z))\pi_{e'_g, z' | e_b, z} \hat{K}_{e_b} + L(z)\pi_{e'_g, z' | e_g, z} \hat{K}_e}{L(z')}$$

In words: the first equation is the average capital stock of unemployed agents next period is the aggregated primary auxilliary policy rules (PAPRs) of the unemployed agents this period plus the aggregated PAPRs of employed agents this period who become unemployed next period, divided by the number of unemployed next period. The second says that the average capital stock of employed agents next period is the aggregated PAPRs of the unemployed agents who become unemployed next period, plus the aggregated PAPRs of those who remain employed, all divided by the number of employed next period.

Having solved the RHS, we can recover the endogenous values of end of period k, k^{end}, associated with each of these points to construct endogenous grid points (see below for a discussion of this method). Then this period's individual policy function is constructed using a one-dimensional piecewise linear spline over k^{end}. Finally, for each $e \in E$ and $z \in Z$, the individual policy function for $k'_{e,z}$ is approximated by a three-dimensional piecewise linear spline in K_e, K_u and k^{end}. The algorithm then compares the $k'_{e,z}$ with the last iteration's value for $k'_{e,z}$. If the two are within a prespecified error tolerance level, ϵ_k, then we say that a stationary policy has been found. Otherwise the individual problem begins again.

B.2.1 The Method of Endogenous Grid Points

Maliar et al. (2010) use the method of endogenous grid points when solving the individual problem. The grid points are endogenous in the sense that we do not have to specify some grid of values and then use a rootfinding algorithm to find the value of c that solves equation B.1. This is a useful technique because rootfinding algorithms are exceptionally slow.

The method works because any arbitrary value of k, call it k_i, will be associated with a marginal valuation at the end of the current period, and it is easy to find the value of c that gives the same marginal value. Construct the end of period's marginal value function $V_{k'}(k, e, z, \bar{K})$ as the right hand side of equation B.1, but with updated employment statuses (since some agents change employment status during the period). Then we can find the value of c that gives the same marginal valuation as:

$$
\begin{aligned}
U'(c) &= \mathcal{V}_{k'}(k, e, z, \bar{K}) \\
\implies c &= U^{-1}(\mathcal{V}_{k'}(k, e, z, \bar{K})) \\
&= \mathcal{V}_{k'}(k, e, z, \bar{K}))^{-1/\sigma}
\end{aligned}
$$

and, using the values just found, we can also retrieve a value for k consistent with this marginal valuation. These new grid points for k are the endogenous individual capital grid, k^{end}.

C. Chapter 3 Supplementary Material

C.1 MPC on a Balanced Panel in the PSID

This appendix contains the first- and second-stage regressions in the main text repeated on a balanced panel. In other words, while the main text allowed different households over the pre-recession and recession periods, this appendix keeps only households that have non-missing data for the full 2002-2012 period. The estimated equations are the same, and the results are qualitatively identical and quantitatively very similar. The only major difference is in the sample size, and as a result, the precision of the estimates.

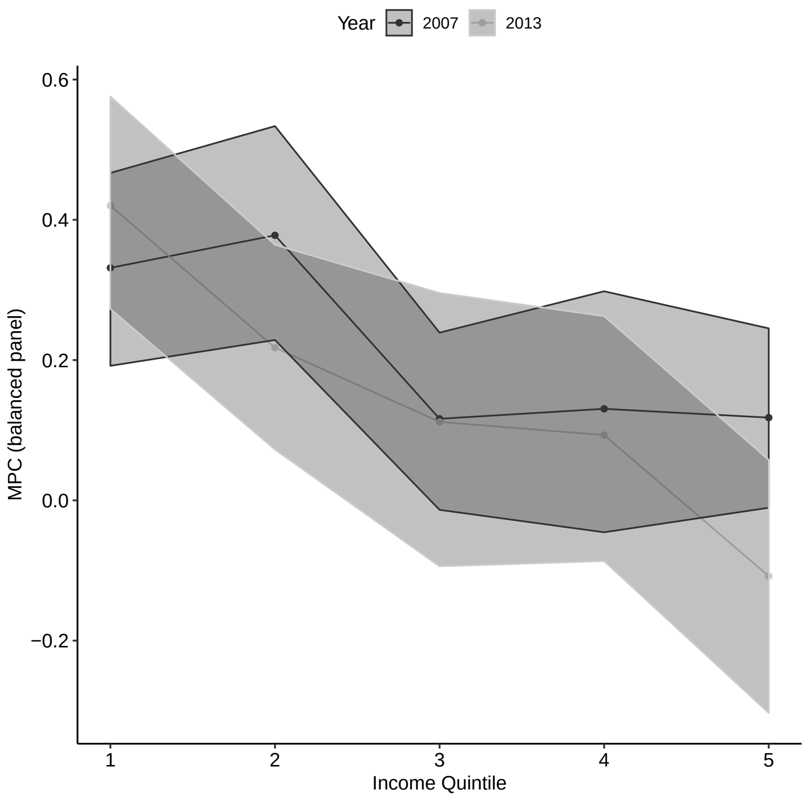

Fig. C.1 Estimated Distribution of MPC year and quintile, balanced panel

Estimated marginal propensity to consume by income quintile and time, balanced panel: recession period (2002-2006), recession (2008-2012)

Table C.1 IV regression: $\Delta c_{i,t}$ 2002-2006 for Income Quintiles (balanced panel)

	$\Delta\widehat{c_{i,t}}$				
	(1)	(2)	(3)	(4)	(5)
$\Delta\widehat{y_{i,t}}$	0.255***	0.350***	0.099	0.099	0.052
	(0.074)	(0.087)	(0.069)	(0.085)	(0.073)
N	553	556	555	555	539
R^2	0.223	0.171	0.059	0.042	0.021
Residual Std. Error	0.082 (df = 551)	0.093 (df = 554)	0.101 (df = 553)	0.111 (df = 553)	0.132 (df = 537)

Notes:
***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Instrumental variable regression of $\Delta\widehat{c}_t$ on $\Delta\widehat{y}_t$ instrumented by $\Delta\widehat{y_{t+1}}$ for the income quintiles, 2002-2006

Table C.2 IV regression: $\Delta c_{i,t}$ 2008-2012 for Income Quintiles (balanced panel)

	$\Delta\widehat{c_{i,t}}$				
	(1)	(2)	(3)	(4)	(5)
$\Delta\widehat{y_{i,t}}$	0.450***	0.302***	0.157	0.105	−0.077
	(0.078)	(0.075)	(0.100)	(0.084)	(0.084)
N	556	554	554	553	543
R^2	0.196	0.077	0.105	0.054	-0.064
Residual Std. Error	0.091 (df = 554)	0.100 (df = 552)	0.118 (df = 552)	0.124 (df = 551)	0.144 (df = 541)

Notes:

***Significant at the 1 percent level.

**Significant at the 5 percent level.

*Significant at the 10 percent level.

Instrumental variable regression of $\Delta\widehat{c_t}$ on $\Delta\widehat{y_t}$ instrumented by $\Delta\widehat{y_{t+1}}$ for the income quintiles, 2008-2012

Table C.3 First Stage Regressions

	$\log(\widehat{c_{it}})$		$\log(\widehat{y_{it}})$	
	2003-2007	2009-2013	2003-2007	2009-2013
	(1)	(2)	(3)	(4)
Year=2004	0.056***		0.035***	
	(0.003)		(0.006)	
Year=2006	0.082***		0.059***	
	(0.005)		(0.005)	
Year=2010		0.006*		0.002
		(0.003)		(0.004)
Year=2012		0.015**		0.022**
		(0.003)		(0.006)
Education=Medium	0.038***	0.037**	0.070***	0.068***
	(0.007)	(0.009)	(0.011)	(0.013)
Education=High	0.111***	0.116***	0.168***	0.191***
	(0.007)	(0.010)	(0.012)	(0.014)
Race=Black	−0.047***	−0.038**	−0.073***	−0.067***
	(0.010)	(0.010)	(0.011)	(0.011)
Race=Other	−0.009	−0.015	−0.053*	−0.076**
	(0.022)	(0.012)	(0.024)	(0.018)
Family Size	0.068***	0.087***	0.091***	0.108***
	(0.006)	(0.005)	(0.006)	(0.006)
Number of Kids	−0.045***	−0.062***	−0.073***	−0.080***
	(0.006)	(0.007)	(0.008)	(0.008)
Status=Unemployed	−0.074**	−0.056***	−0.129**	−0.108***
	(0.020)	(0.010)	(0.031)	(0.019)
Status=Retired	−0.059***	−0.081***	−0.102***	−0.118***
	(0.009)	(0.007)	(0.011)	(0.011)
Status=Inactive	−0.069***	−0.098***	−0.130***	−0.153***
	(0.011)	(0.009)	(0.011)	(0.015)
Extra Family Income	0.017*	0.003	0.031**	0.028*
	(0.007)	(0.009)	(0.008)	(0.010)
Region=Midwest	−0.043**	−0.055***	−0.041*	−0.059**
	(0.013)	(0.012)	(0.015)	(0.014)
Region=South	−0.025	−0.037**	−0.031	−0.043*
	(0.015)	(0.013)	(0.020)	(0.017)
Region=West	−0.018	−0.048**	−0.034*	−0.059**
	(0.014)	(0.012)	(0.013)	(0.013)
Kids outside Family Unit	0.022*	0.034***	0.058**	0.070***
	(0.009)	(0.005)	(0.015)	(0.010)
Poor-HtM	−0.081***	−0.064***	−0.136***	−0.130***
	(0.007)	(0.009)	(0.011)	(0.014)
Rich-HtM	−0.012	−0.013	−0.066***	−0.064***
	(0.006)	(0.008)	(0.009)	(0.012)
Total Wealth ($1000s)	0.0002*	0.0003*	0.0005*	0.001**
	(0.0001)	(0.0001)	(0.0002)	(0.0002)
Constant	11.615***	11.659***	11.723***	11.666***
	(0.044)	(0.035)	(0.070)	(0.079)
Year of Birth	Yes	Yes	Yes	Yes
N	8,373	8,373	8,373	8,373

Notes:

***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Survey-weighted generalised least squares regression for the years 2002, 2004, 2006, 2008, 2009, 2011 (columns 2 and 4) in the PSID balanced panel.